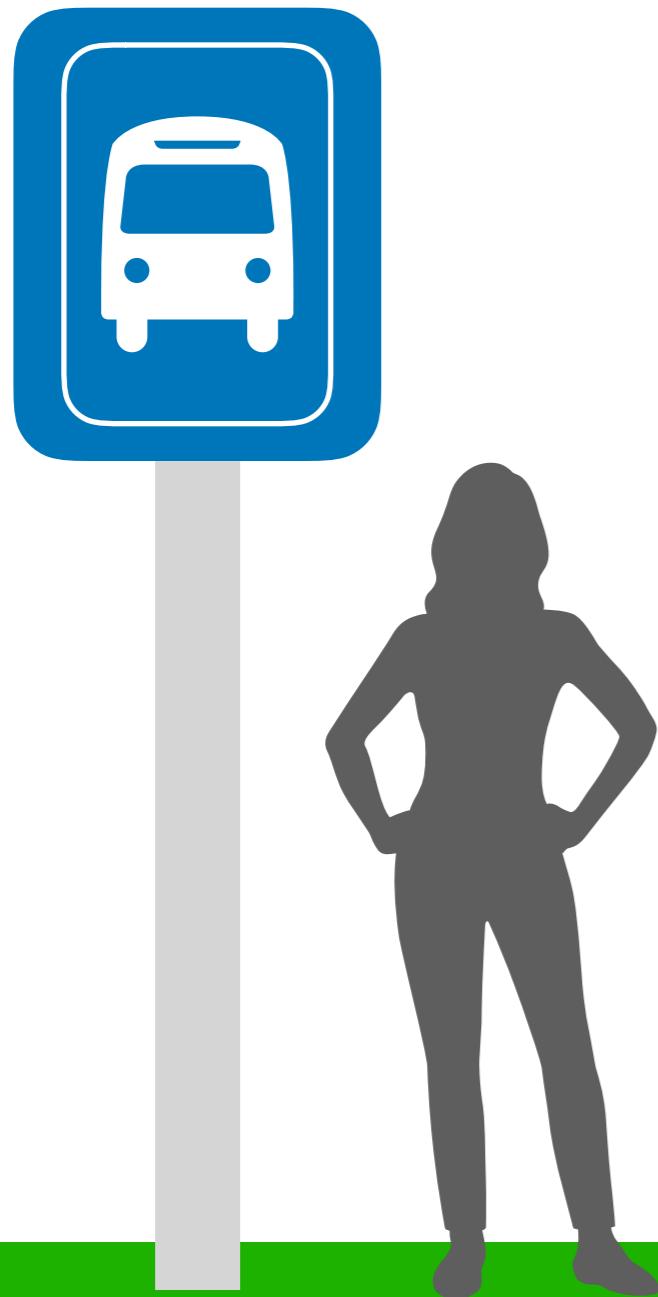


Lecture 12

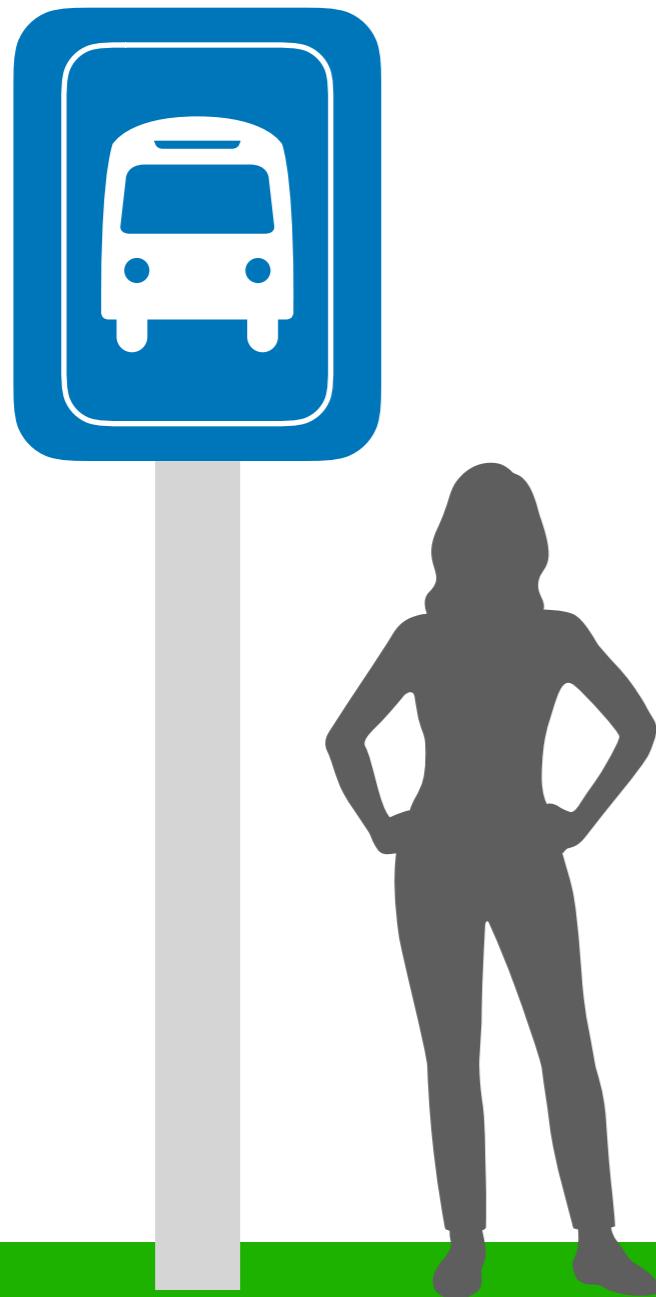
Bayesian inference
Botany 563 – Spring 2021

- **Previous class check-up:**
 - We reviewed the distance, parsimony and likelihood methods and their strengths and weaknesses
- **Learning Objectives:** At the end of today's session, you will be able to
 - Explain the main characteristics of Bayesian inference for phylogenetics
 - Understand the role that priors, sample size and convergence play in the performance of Bayesian inference
 - Learn how to use PhyloBayes and/or MrBayes
- **Pre-class work**
 - Read HAL 1.4 and Nascimento et al (2017)

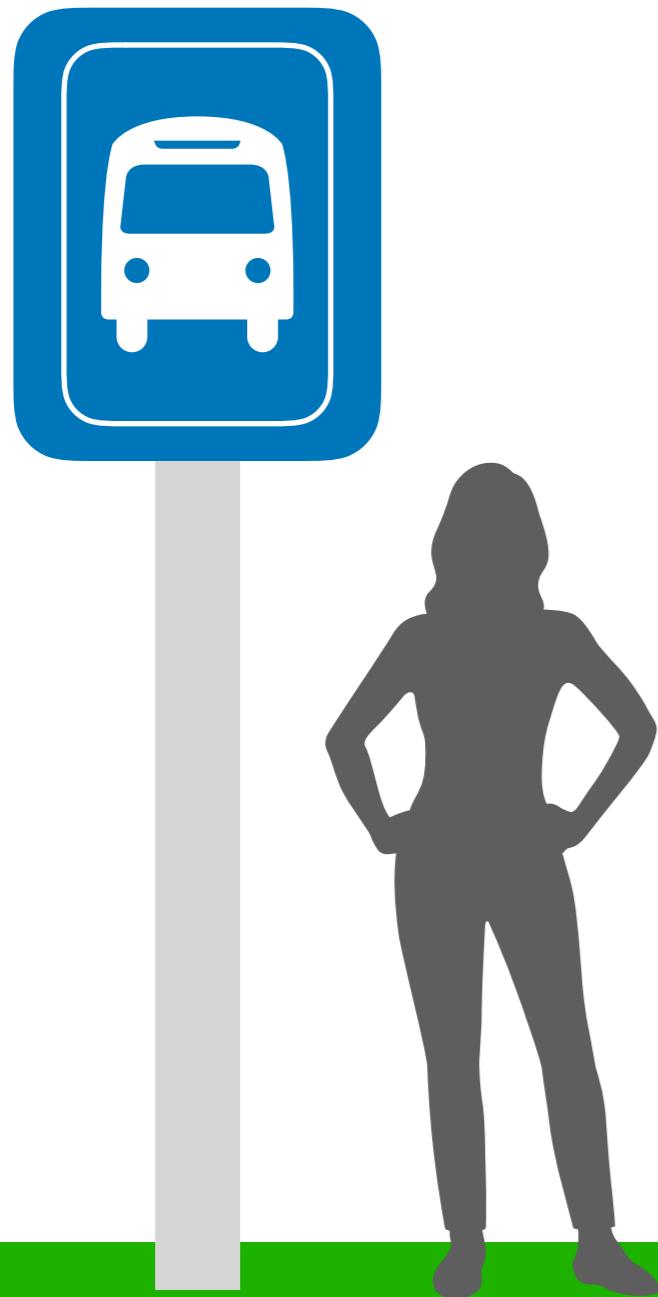
A familiar example



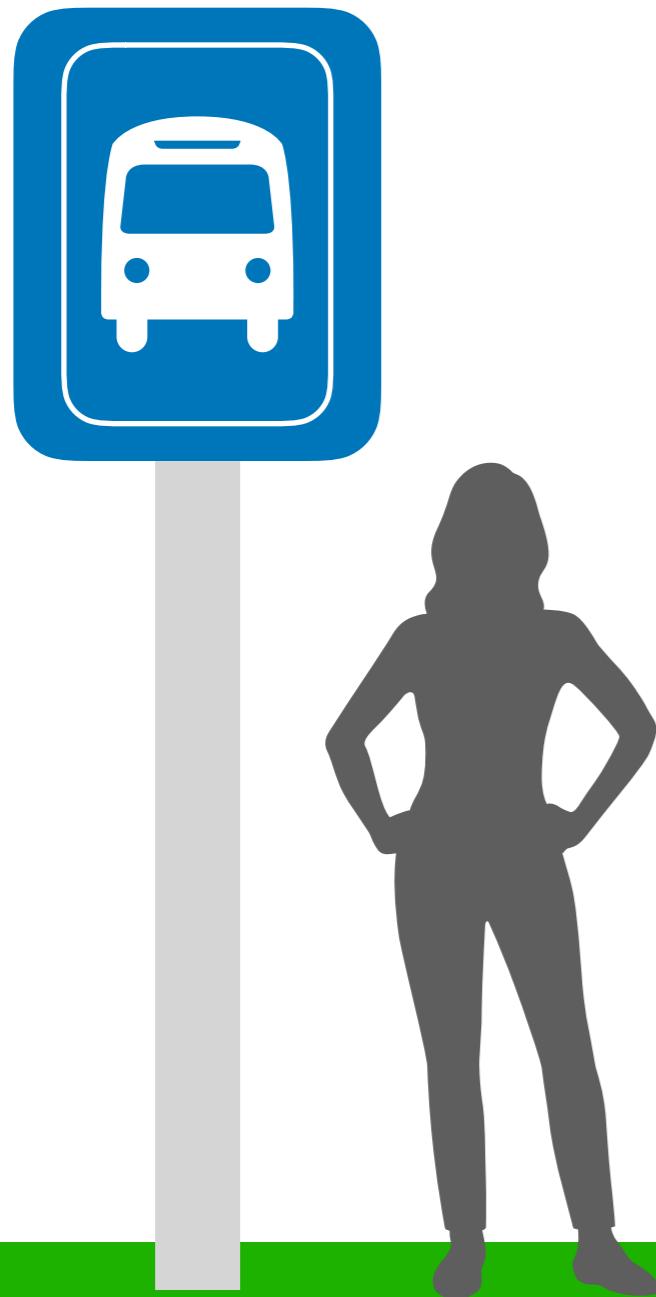
A familiar example



A familiar example



A familiar example



A familiar example

$X_i = \text{Number of bikes seen on day } i$

$$X_i \sim \text{Poisson}(\lambda)$$

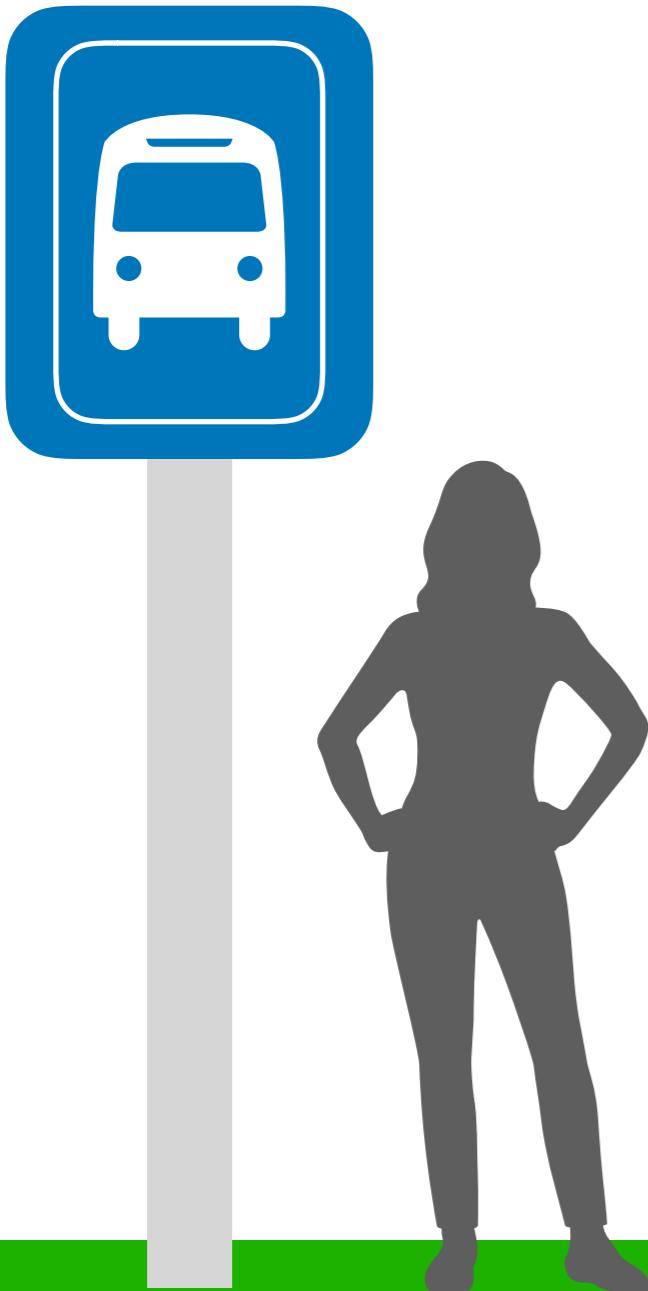
$$P(X_i = k) = \frac{e^{-\lambda} \lambda^k}{k!}$$

We collect data on n days:

$$X_1, X_2, \dots, X_n$$

We want the MLE for λ

1. We need the likelihood function
2. We need to maximize the likelihood function



A familiar example

$X_i = \text{Number of bikes seen on day } i$

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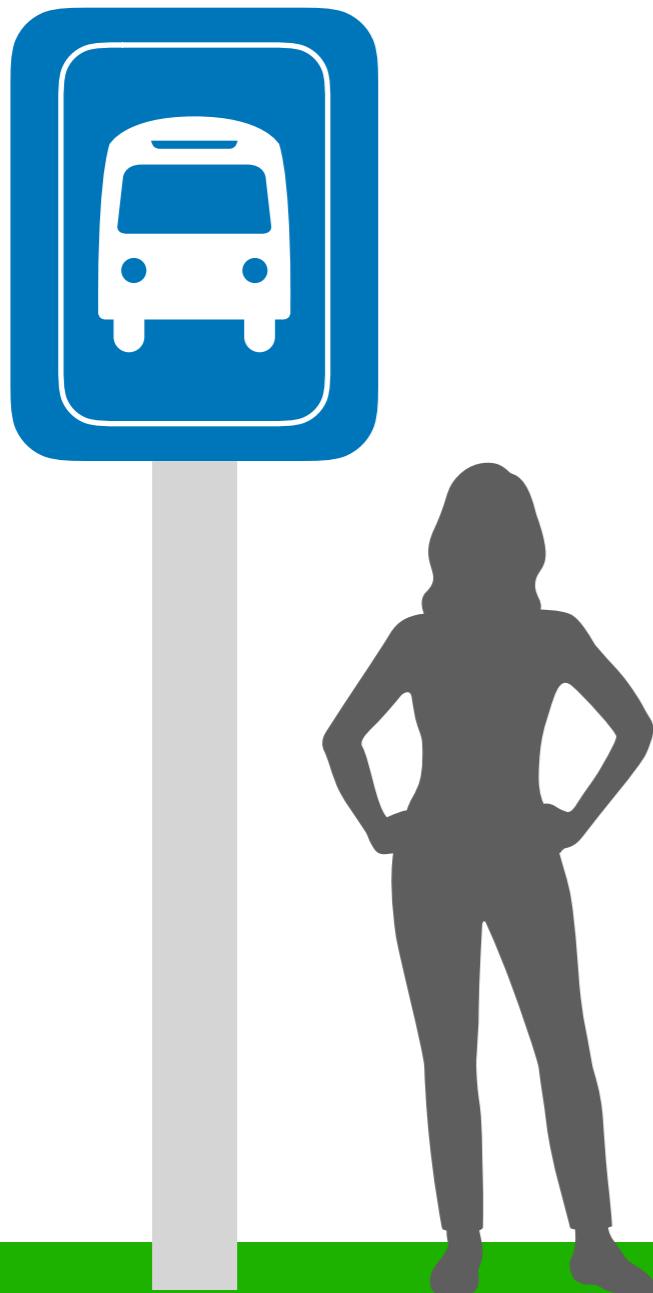
$$X_1, X_2, \dots, X_n$$

Sequences

We want the MLE for λ

Tree, BL, Q

1. We need the likelihood function
2. We need to maximize the likelihood function



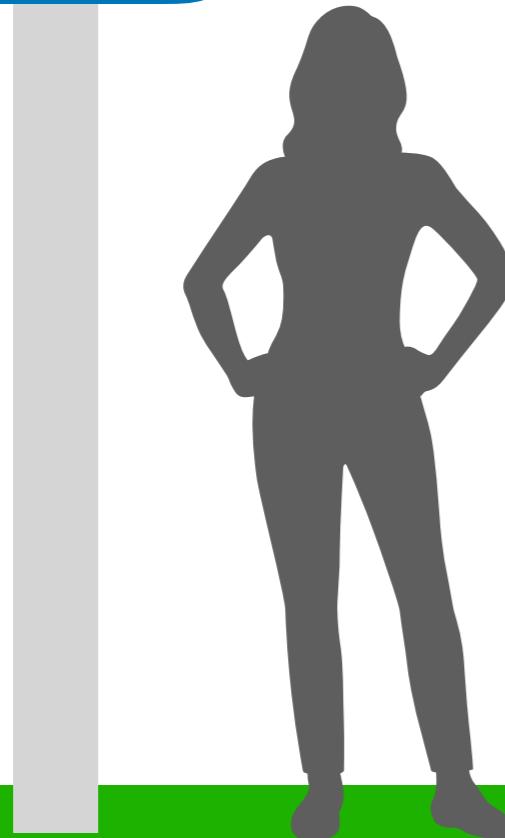
A familiar example

$X_i = \text{Number of bikes seen on day } i$



$$X_i \sim \text{Poisson}(\lambda) \quad P(X_i = k) = \frac{e^{-\lambda} \lambda^k}{k!}$$

We collect data on n days: X_1, X_2, \dots, X_n



A familiar example

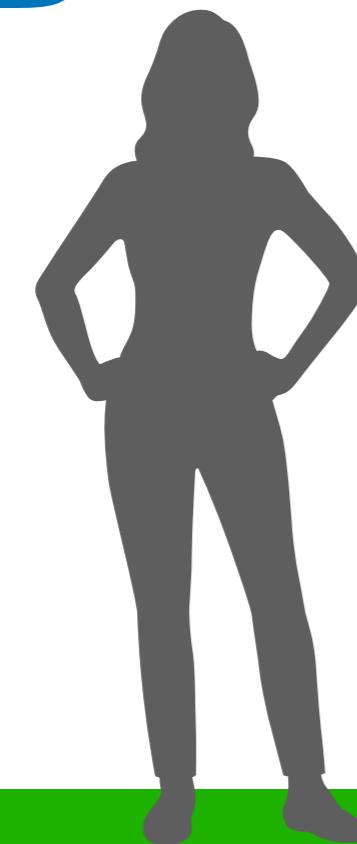
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$$X_i \sim Poisson(\lambda) \quad P(X_i = k) = \frac{e^{-\lambda} \lambda^k}{k!}$$

We collect data on n days: X_1, X_2, \dots, X_n

$$L(\lambda) = \prod_{i=1}^n \frac{e^{-\lambda} \lambda^{x_i}}{x_i!} = \frac{e^{-n\lambda} \lambda^{\sum x_i}}{\prod x_i!}$$



A familiar example

$X_i = \text{Number of bikes seen on day } i$

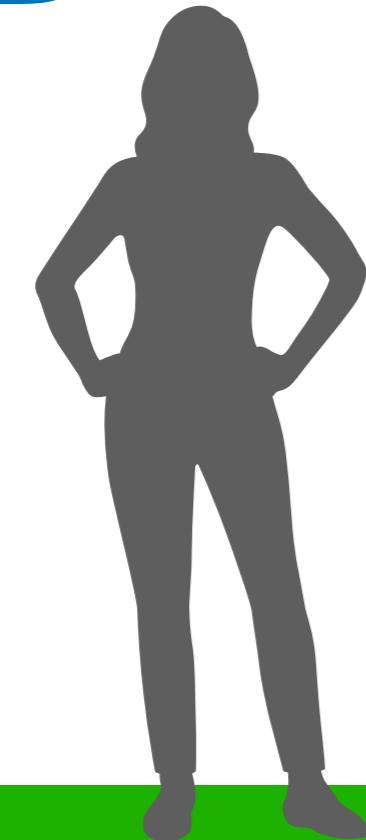


$$X_i \sim \text{Poisson}(\lambda) \quad P(X_i = k) = \frac{e^{-\lambda} \lambda^k}{k!}$$

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$$l(\lambda) = -n\lambda + (\sum x_i) \log(\lambda) - \log(\prod x_i!)$$



A familiar example

$X_i = \text{Number of bikes seen on day } i$



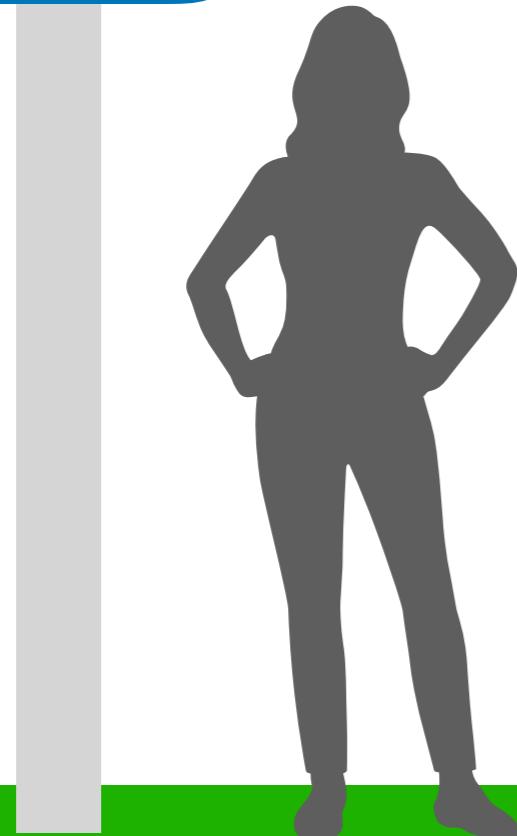
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$$l'(\lambda) = -n + \frac{\sum x_i}{\lambda} = 0$$



A familiar example

X_i = Number of bikes seen on day i



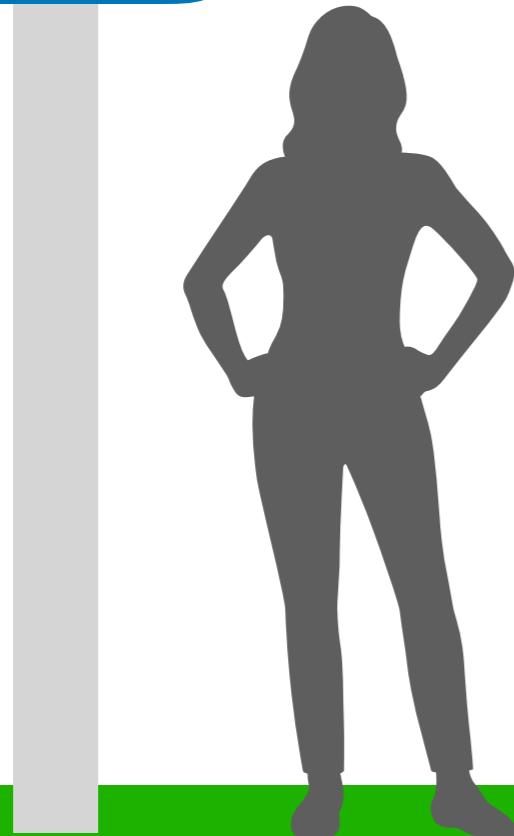
$$X_i \sim \text{Poisson}(\lambda) \quad P(X_i = k) = \frac{e^{-\lambda} \lambda^k}{k!}$$

We collect data on n days: X_1, X_2, \dots, X_n

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$$l(\lambda) = -n\lambda + (\sum x_i) \log(\lambda) - \log(\prod x_i!)$$

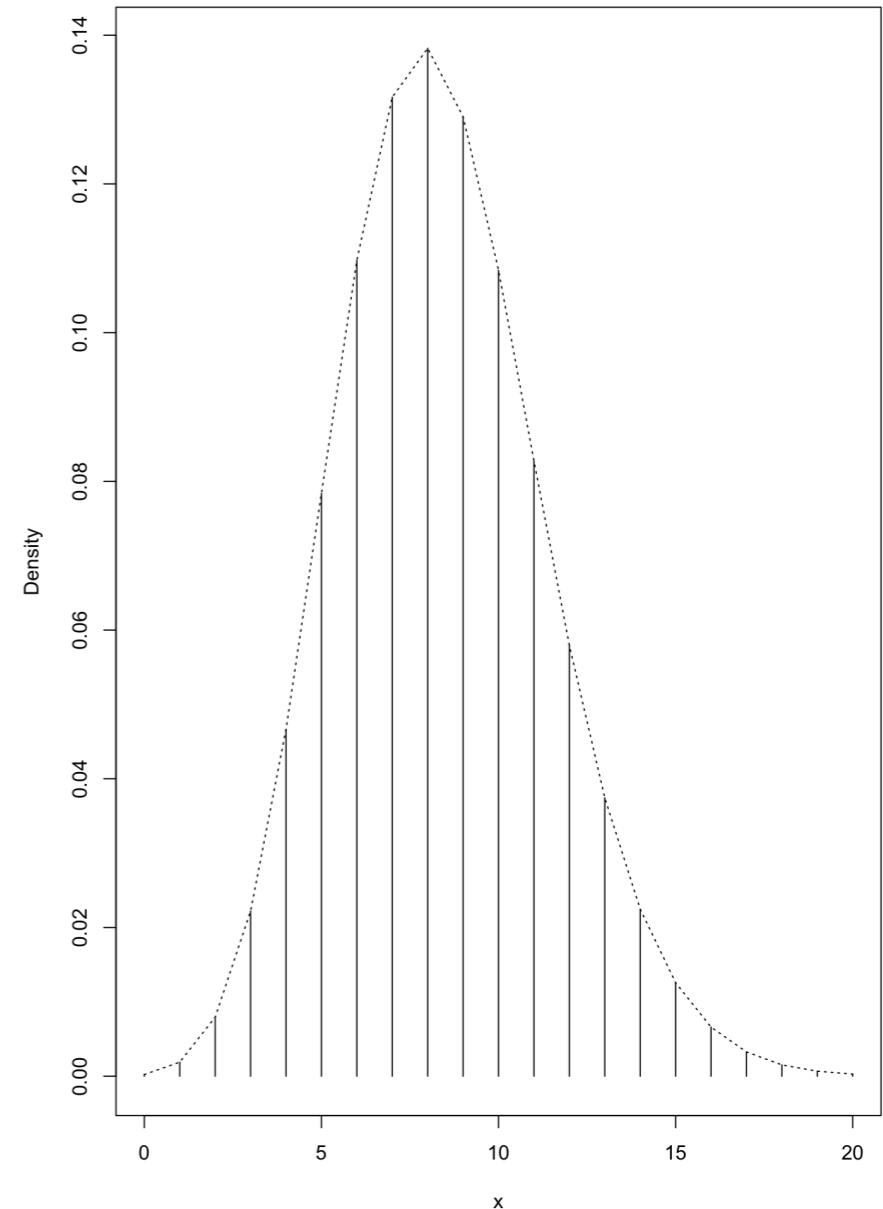
$$l'(\lambda) = -n + \frac{\sum x_i}{\lambda} = 0 \rightarrow \hat{\lambda} = \frac{\sum x_i}{n}$$



Bayesian: Likelihood 2.0

Information in the data

Likelihood

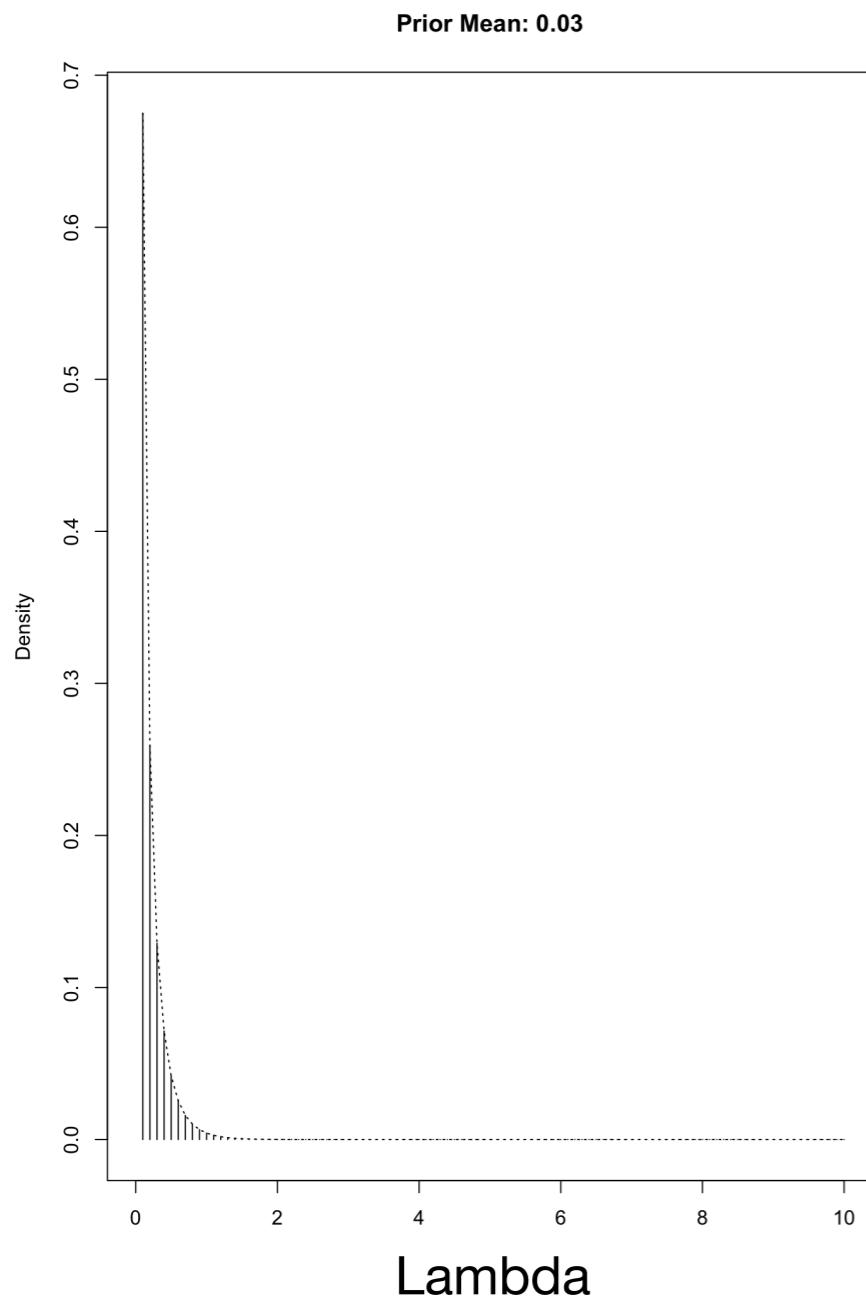


$$\hat{\lambda} = 8.4$$

Bayesian: Likelihood 2.0

Your knowledge

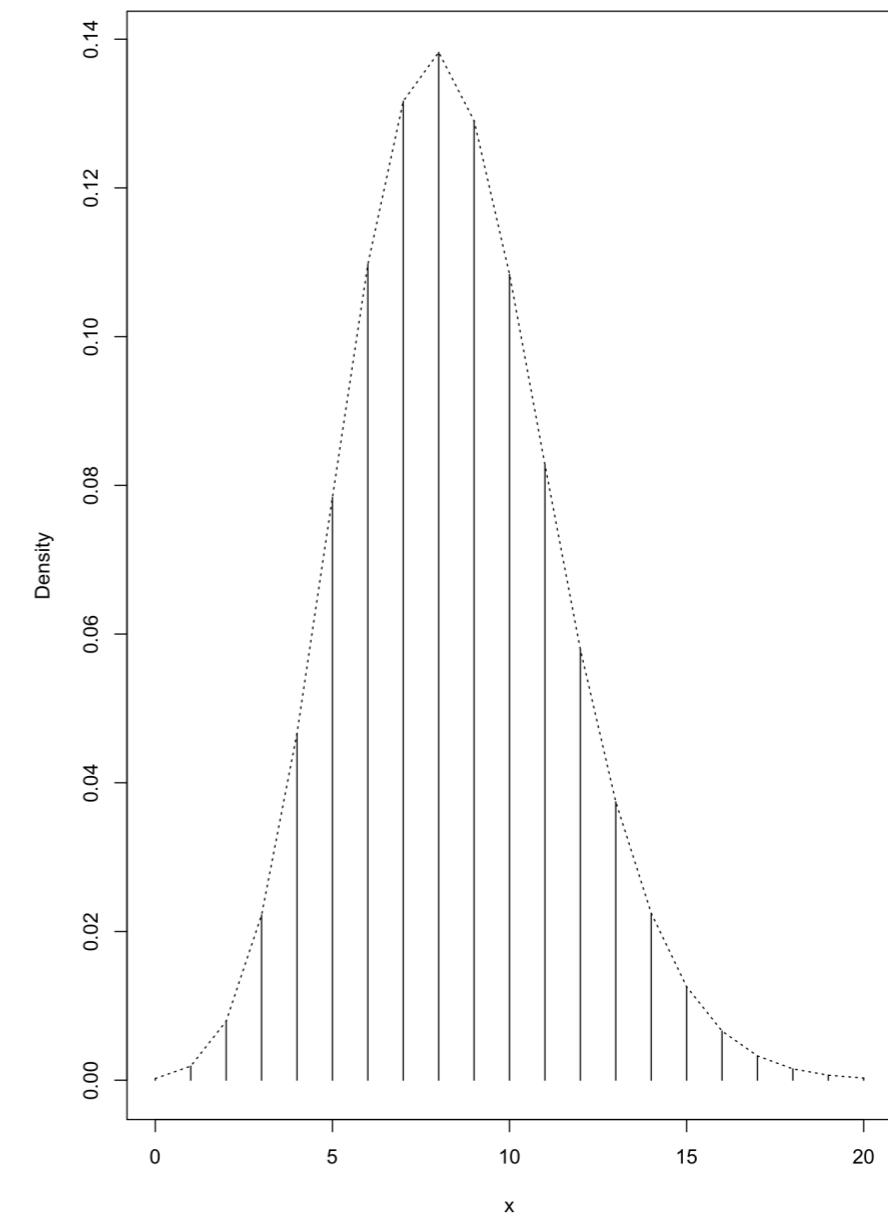
Prior



$$\lambda \sim \text{Gamma}(\alpha = 0.1, \beta = 3.3)$$

Information in the data

Likelihood



$$\hat{\lambda} = 8.4$$

Bayesian: Likelihood 2.0

Your knowledge

Prior

Information in the data

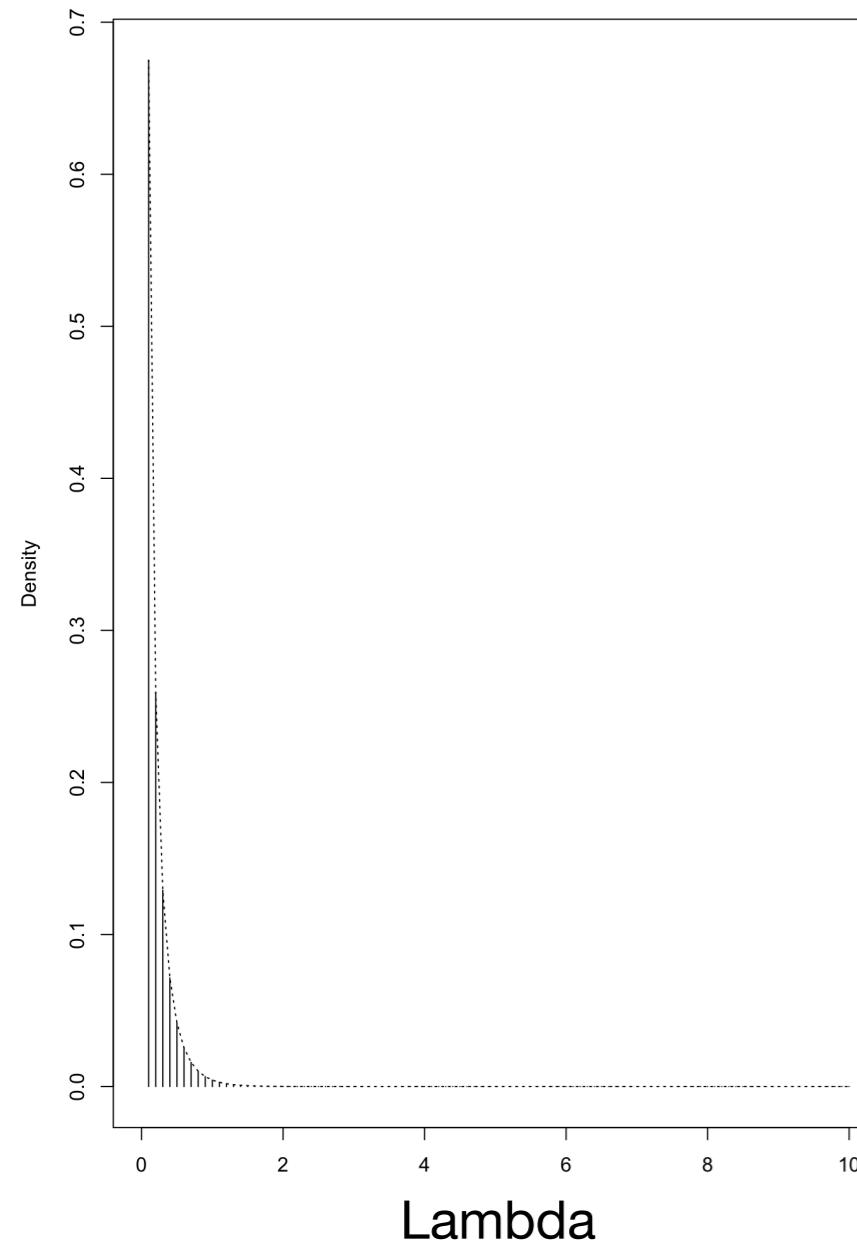
Likelihood

Inference on parameter

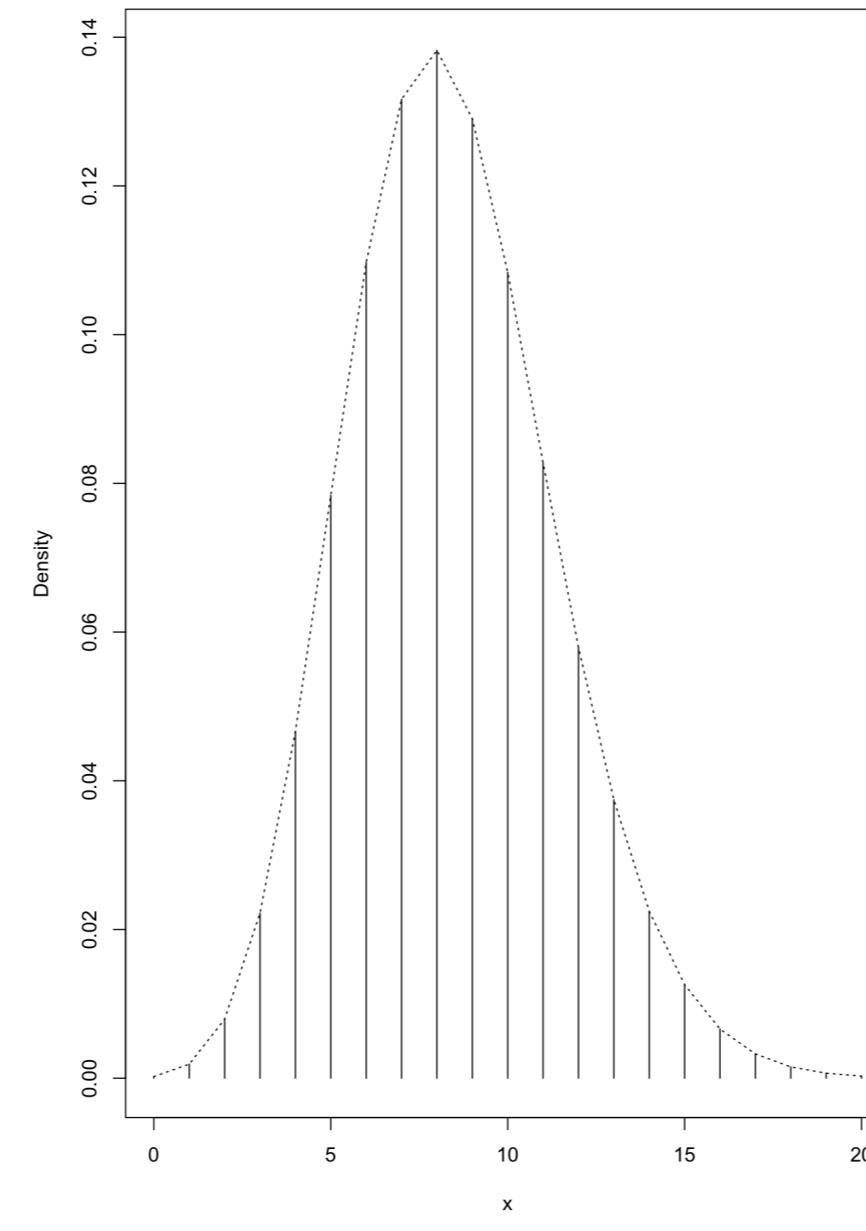
Posterior

Prior Mean: 0.03

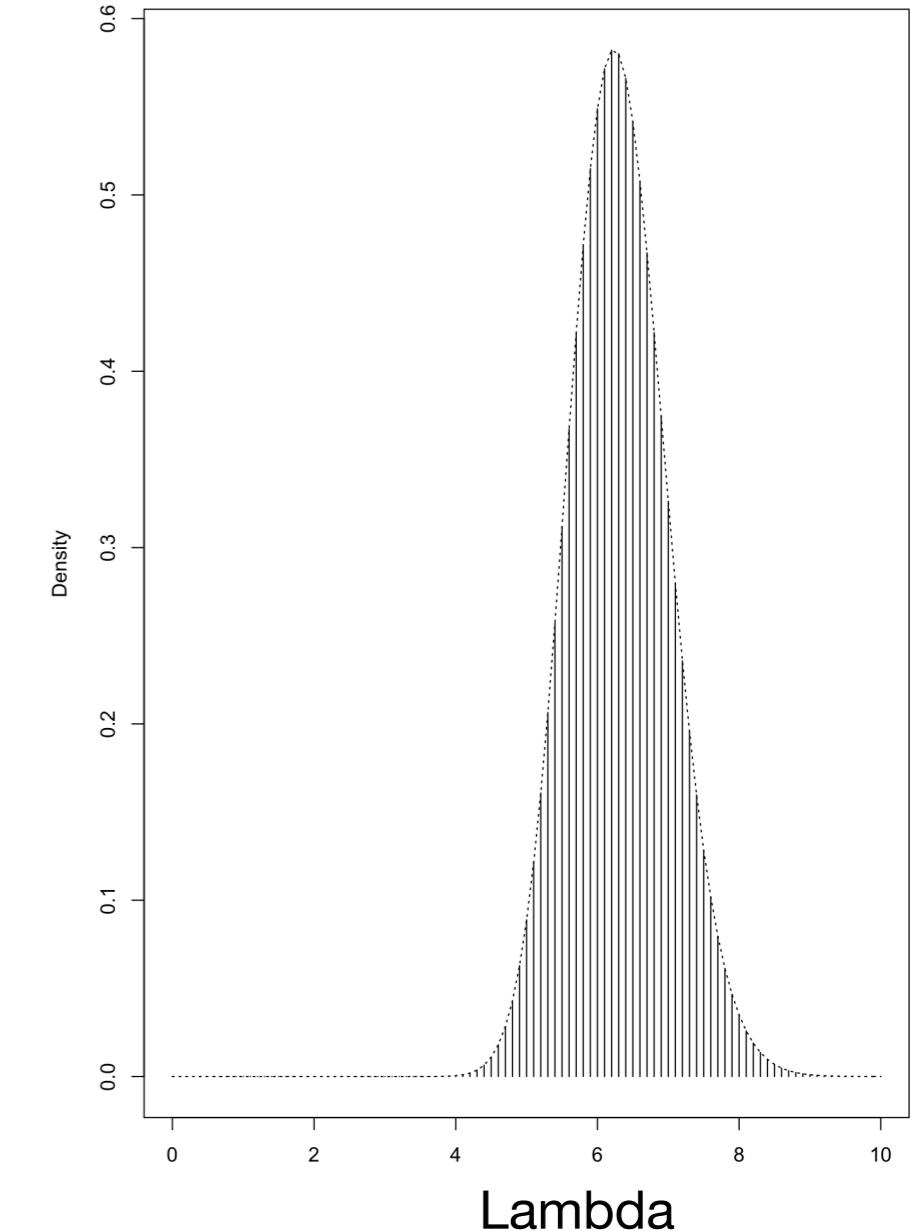
Posterior Mean: 6.31



$\lambda \sim Gamma(\alpha = 0.1, \beta = 3.3)$



$$\hat{\lambda} = 8.4$$



$\lambda | \mathbf{X} \sim Gamma(\alpha = 0.1 + \sum x_i, \beta = 3.3 + n)$

Bayesian: Likelihood 2.0

- Incorporate prior knowledge
- You get a distribution, not just a point estimate

Your knowledge

Prior

Prior Mean: 0.03

Information in the data

Likelihood

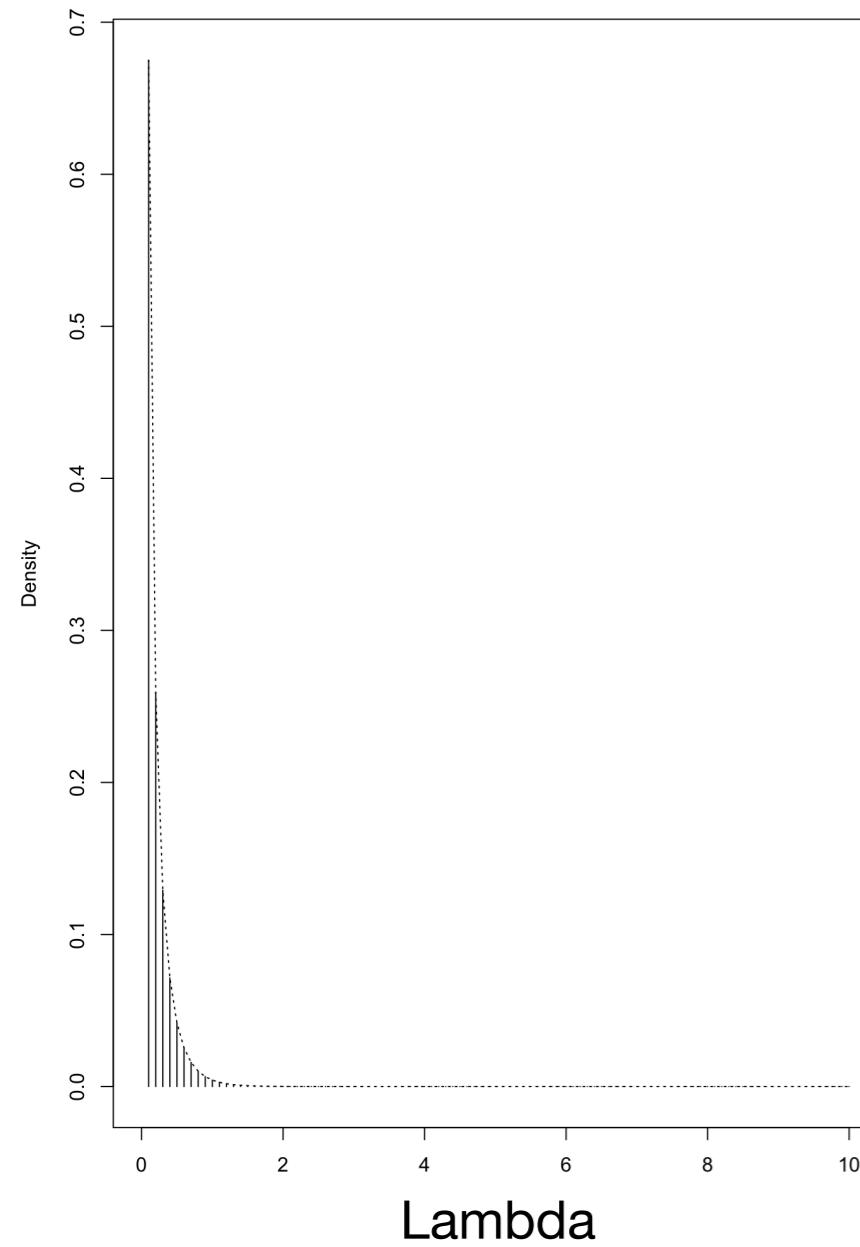
+

Inference on parameter

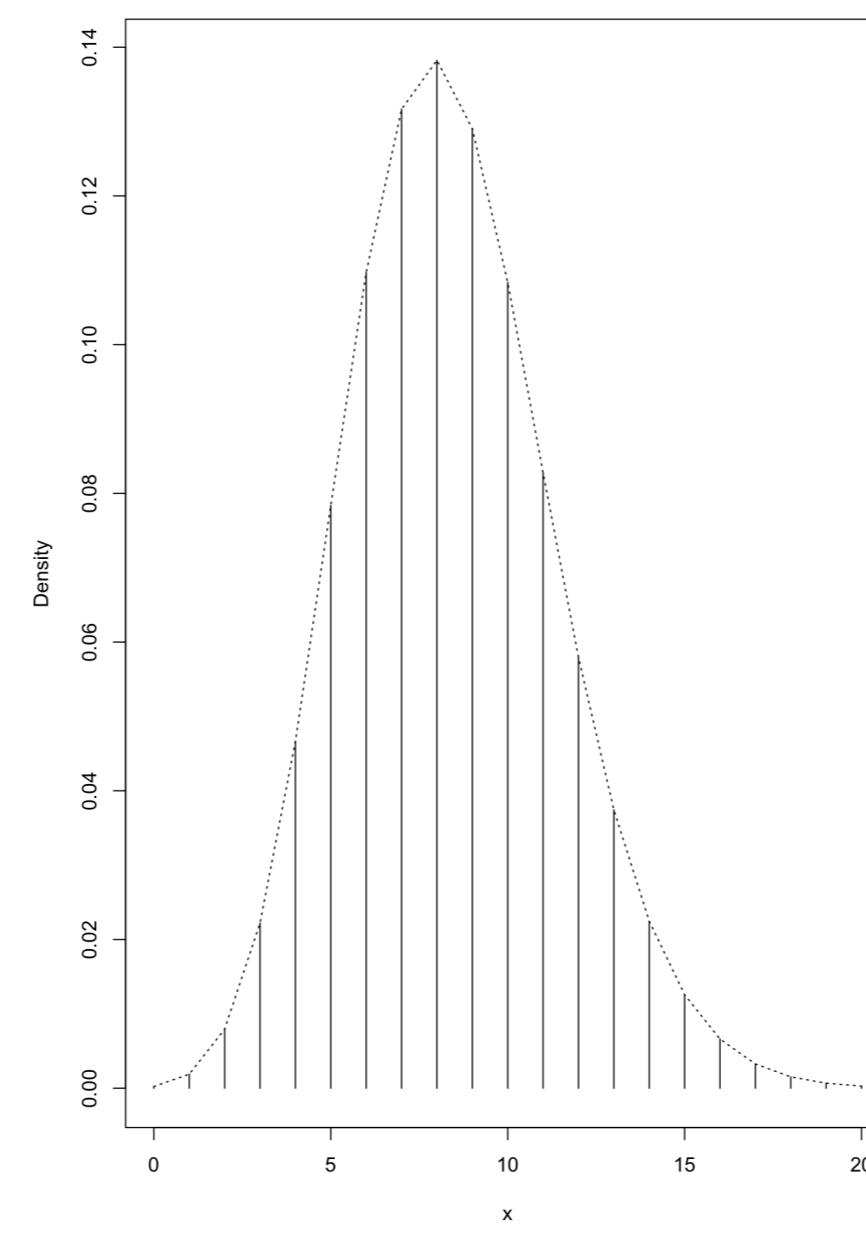
Posterior

=

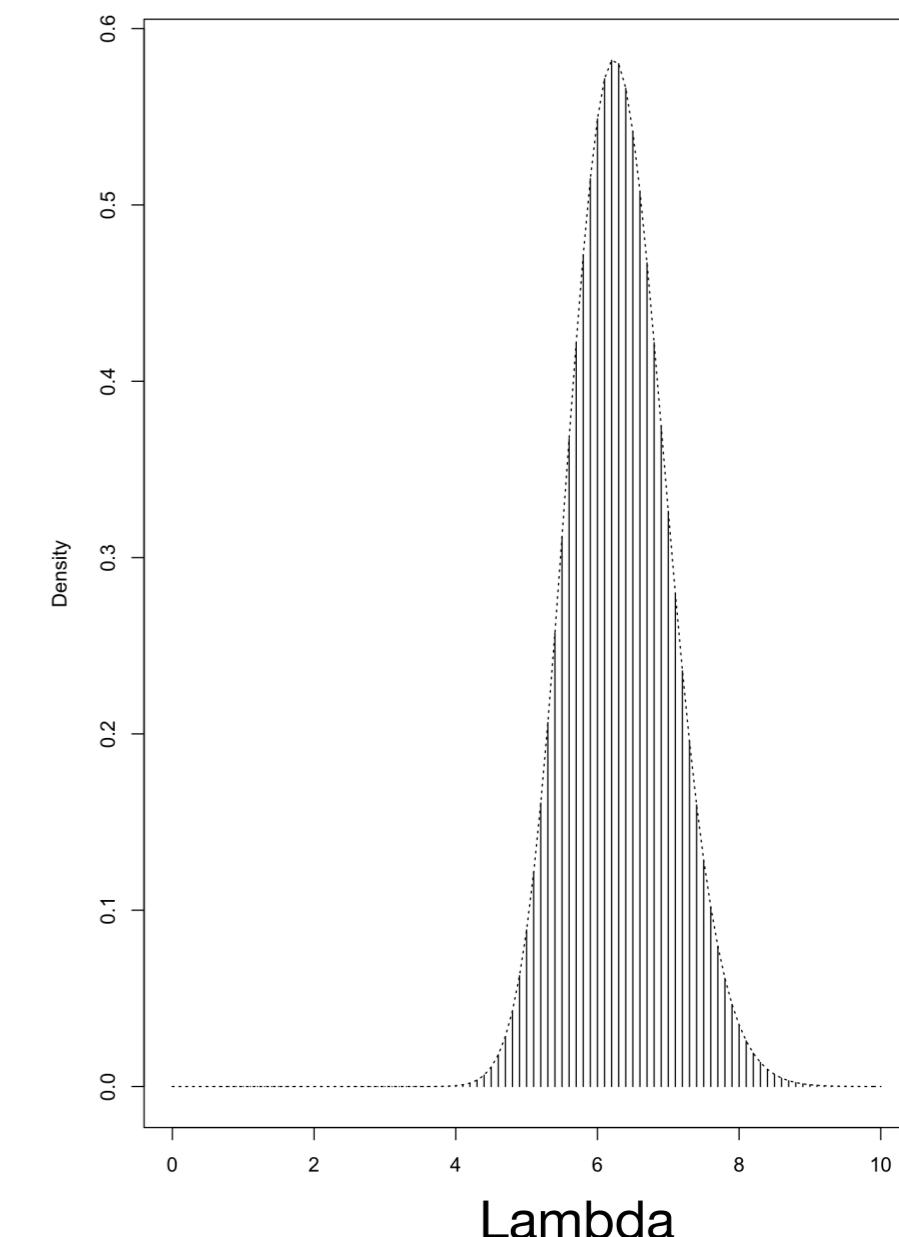
Posterior Mean: 6.31



$\lambda \sim Gamma(\alpha = 0.1, \beta = 3.3)$



$$\hat{\lambda} = 8.4$$



$\lambda | \mathbf{X} \sim Gamma(\alpha = 0.1 + \sum x_i, \beta = 3.3 + n)$

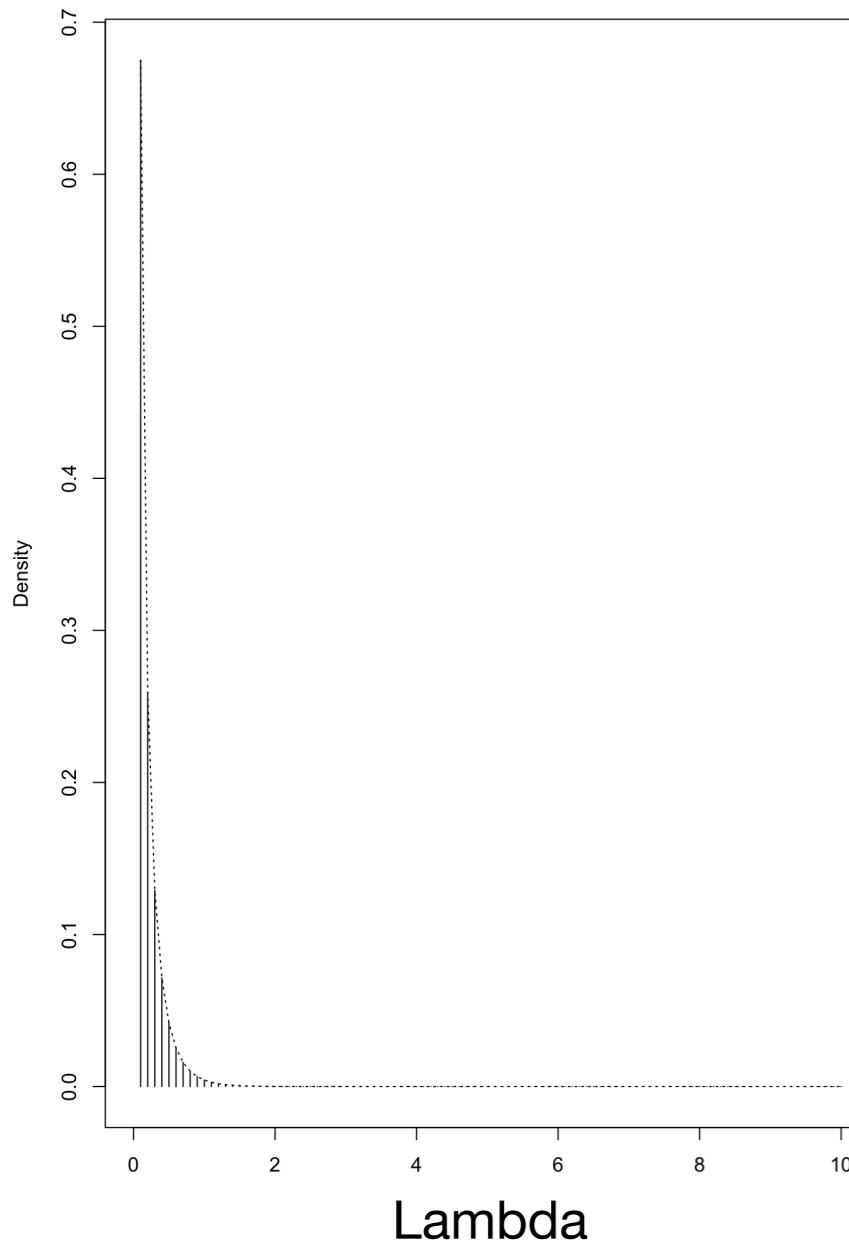
Bayesian: Likelihood 2.0

- Incorporate prior knowledge
- You get a distribution, not just a point estimate

Your knowledge

Prior

Prior Mean: 0.03

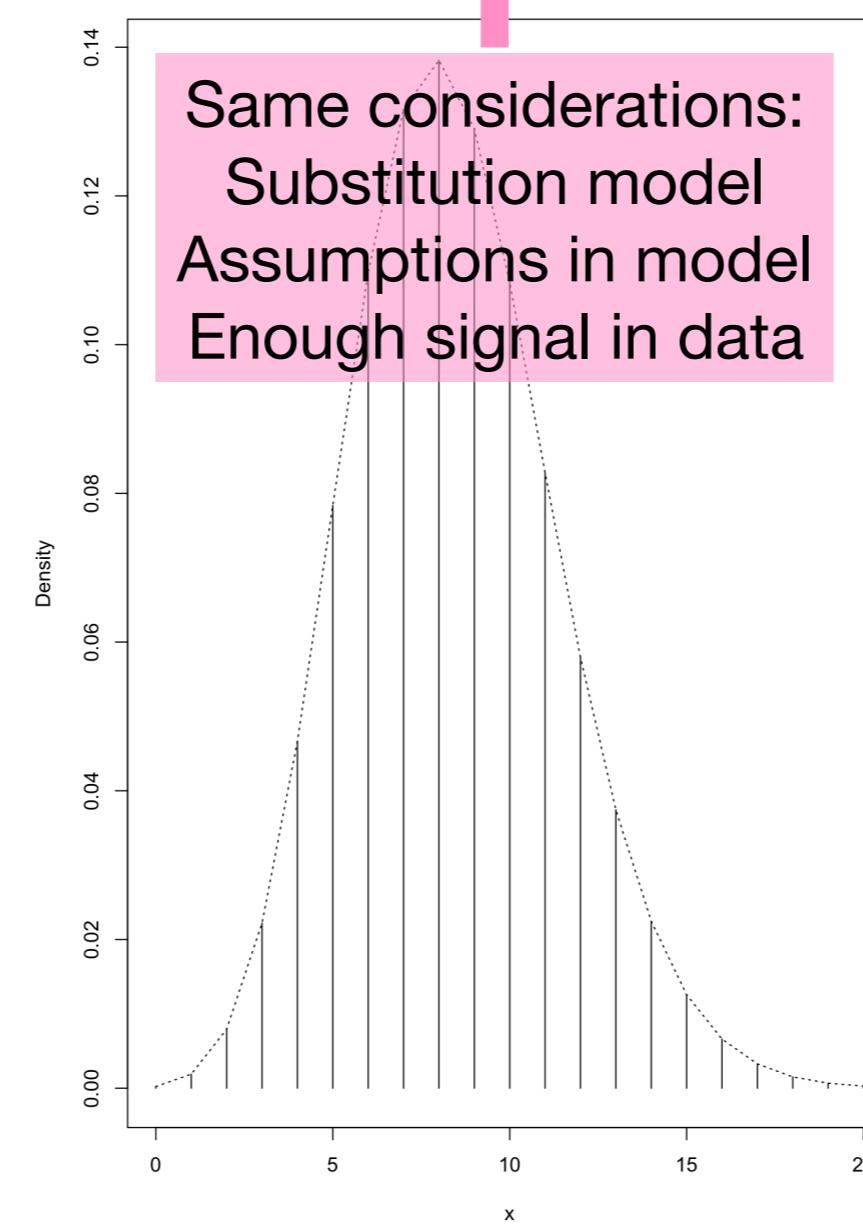


Information in the data

Likelihood



Same considerations:
Substitution model
Assumptions in model
Enough signal in data



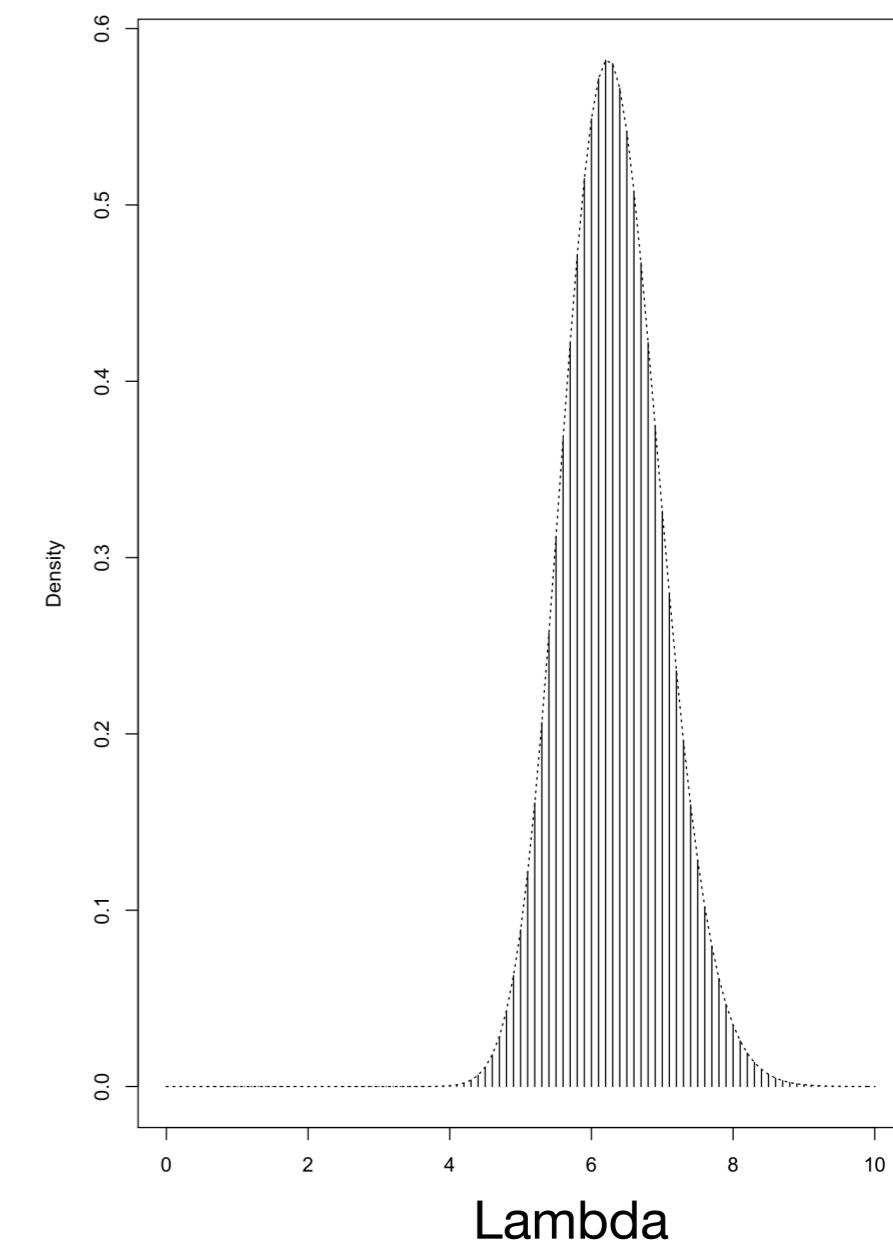
$$\lambda \sim \text{Gamma}(\alpha = 0.1, \beta = 3.3)$$

$$\hat{\lambda} = 8.4$$

Inference on parameter

Posterior

Posterior Mean: 6.31



$$\lambda | \mathbf{X} \sim \text{Gamma}(\alpha = 0.1 + \sum x_i, \beta = 3.3 + n)$$

Bayesian: Likelihood 2.0

- Incorporate prior knowledge
- You get a distribution, not just a point estimate

Your knowledge

Prior

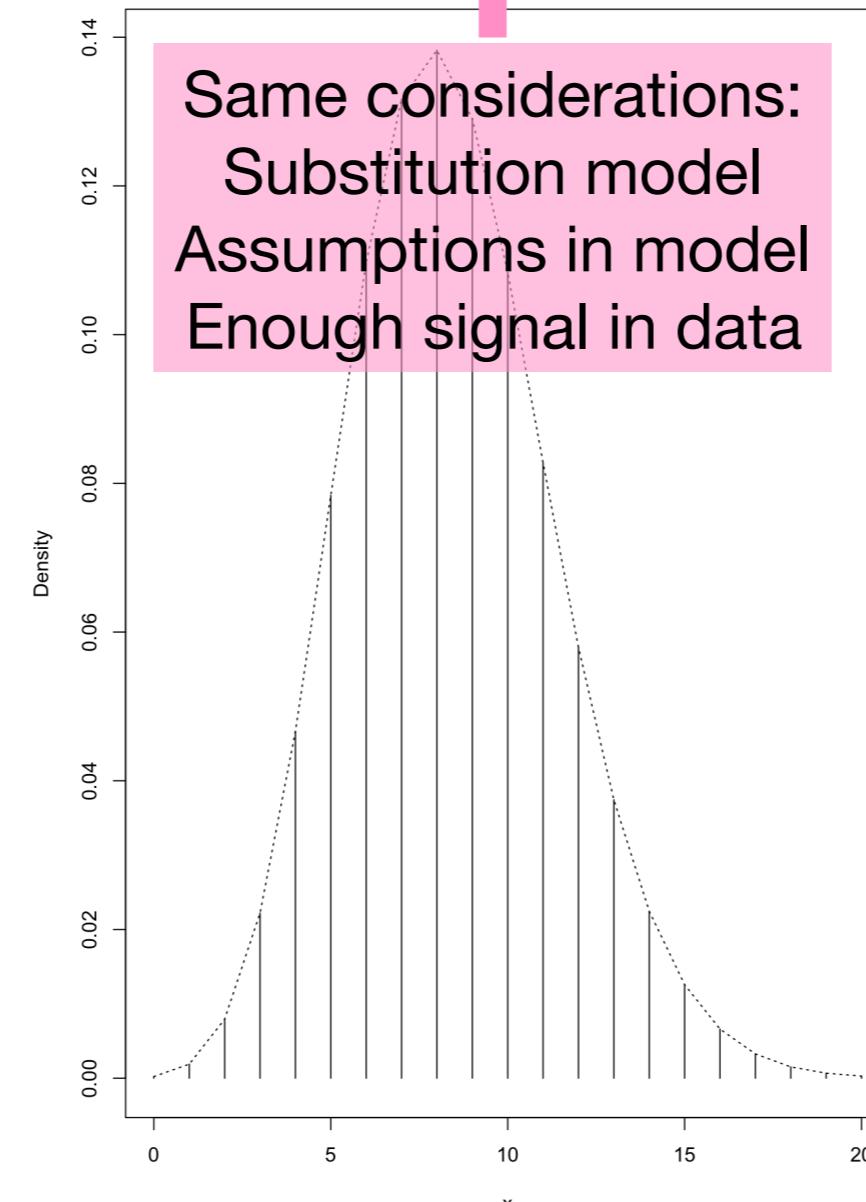
Prior Mean: 0.03

Information in the data

Likelihood

New considerations:
Which prior model?
Assumptions in model
How does this affect inference?

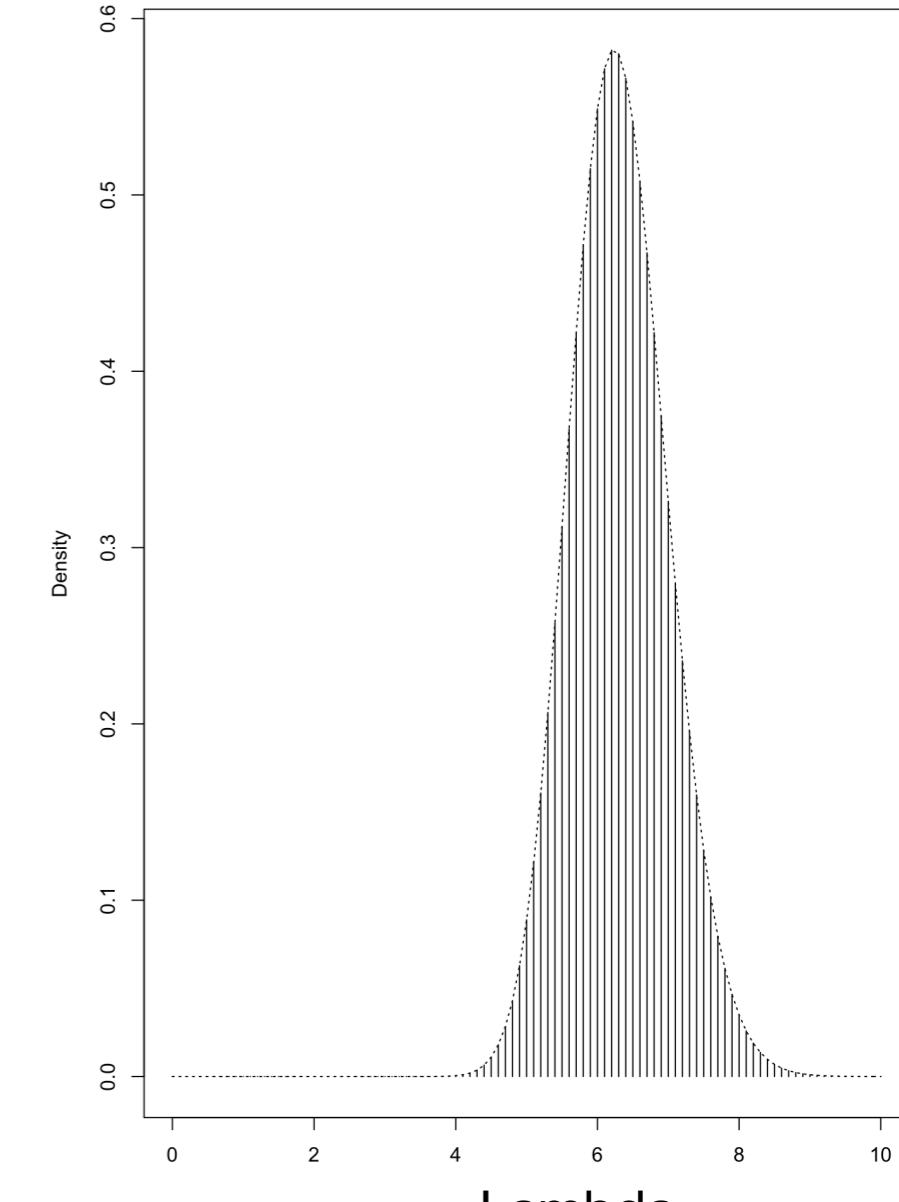
+



Inference on parameter

Posterior

Posterior Mean: 6.31

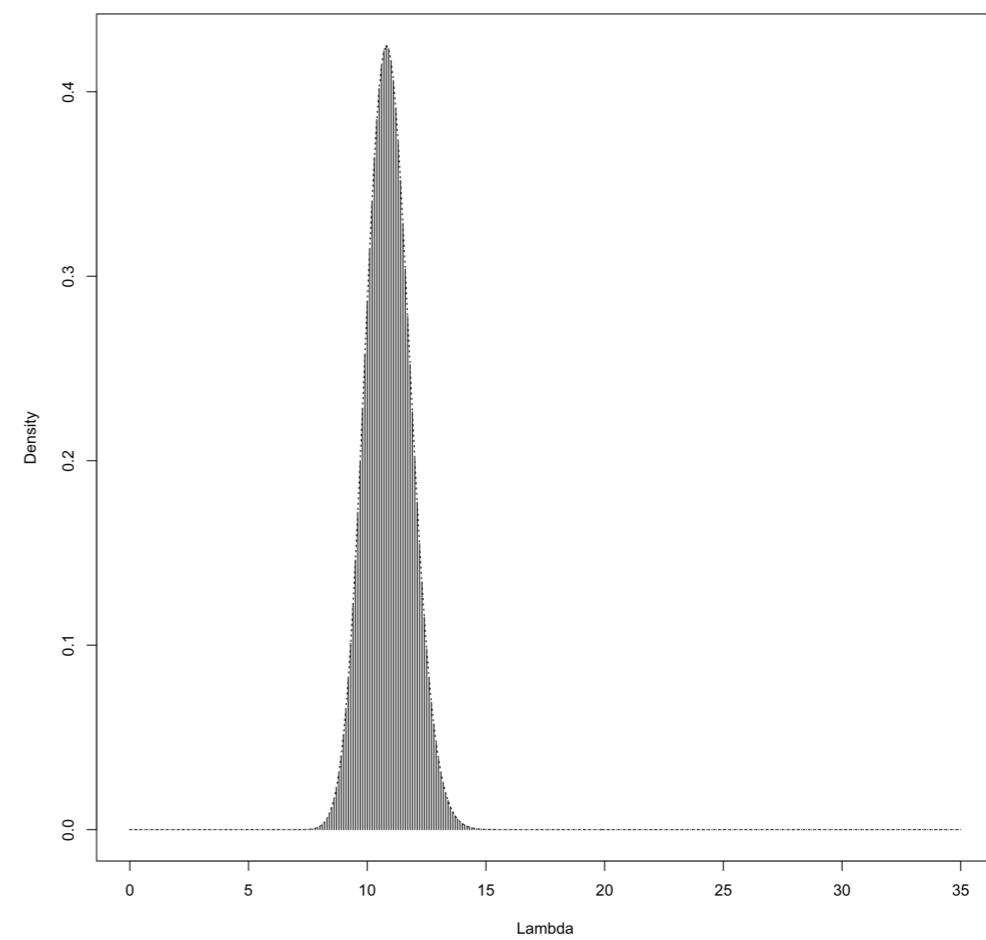
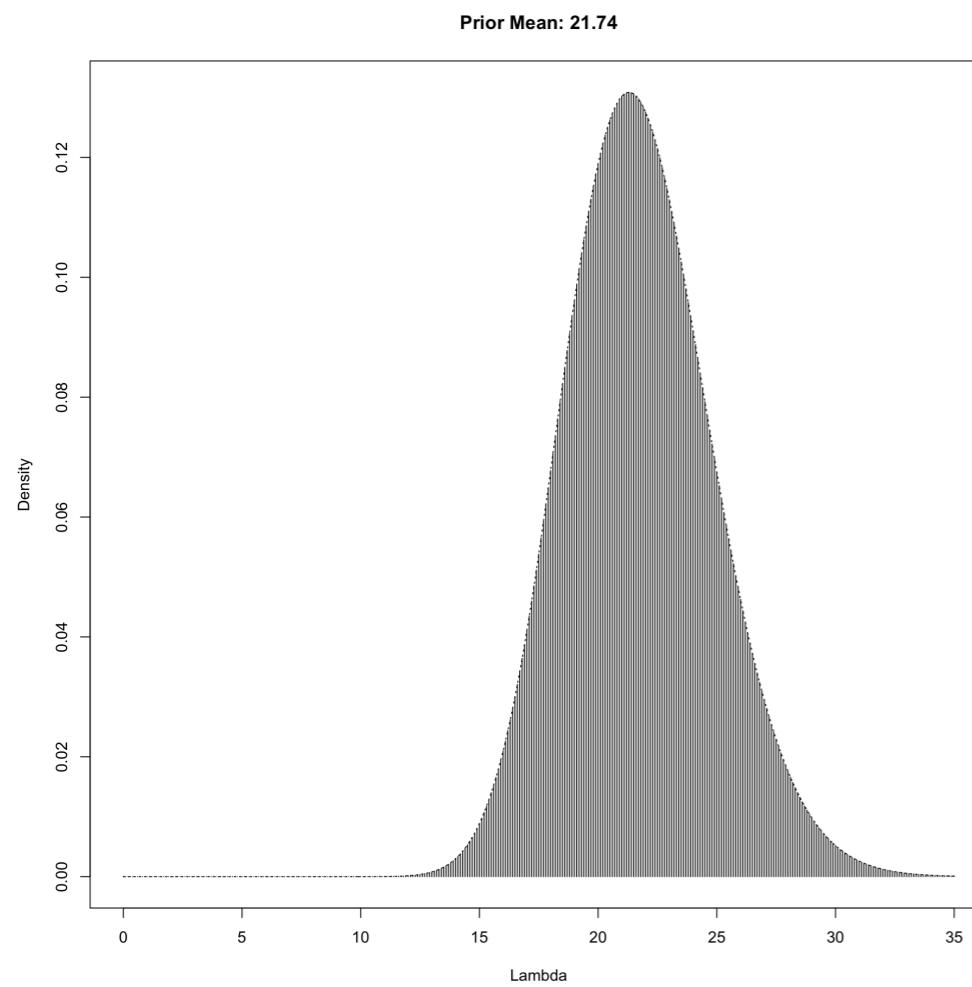
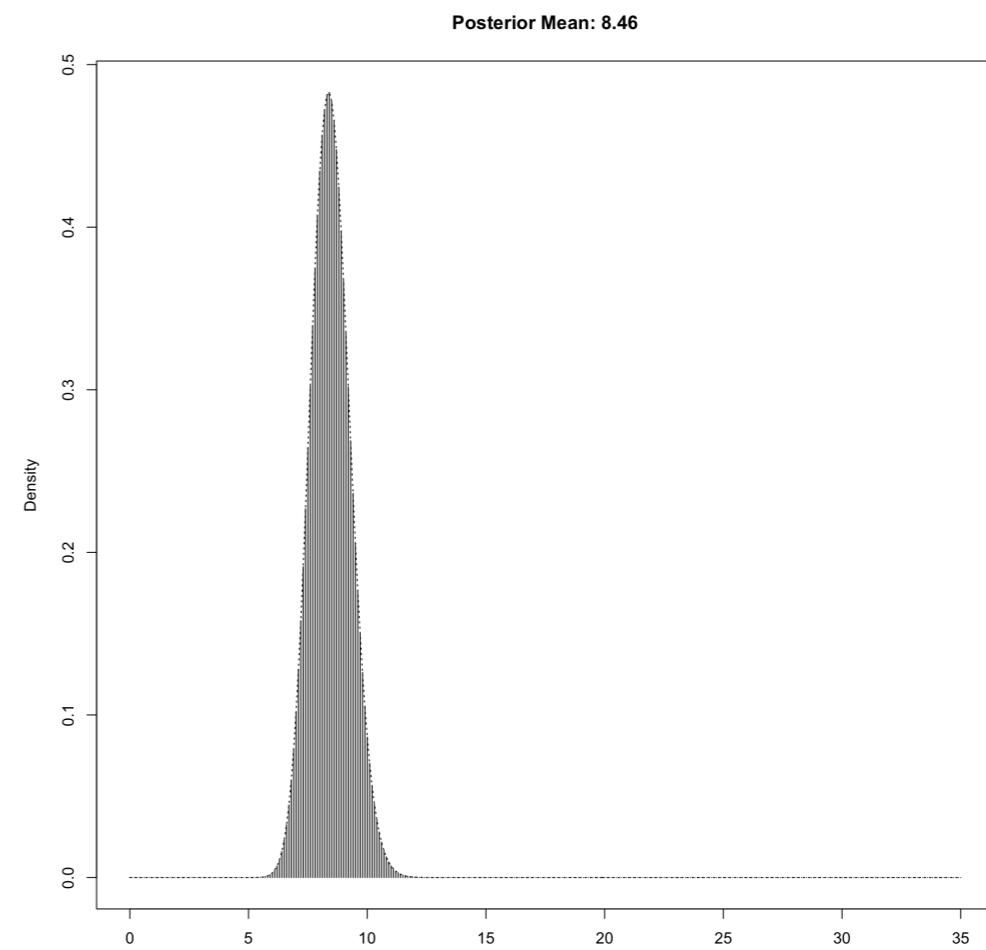
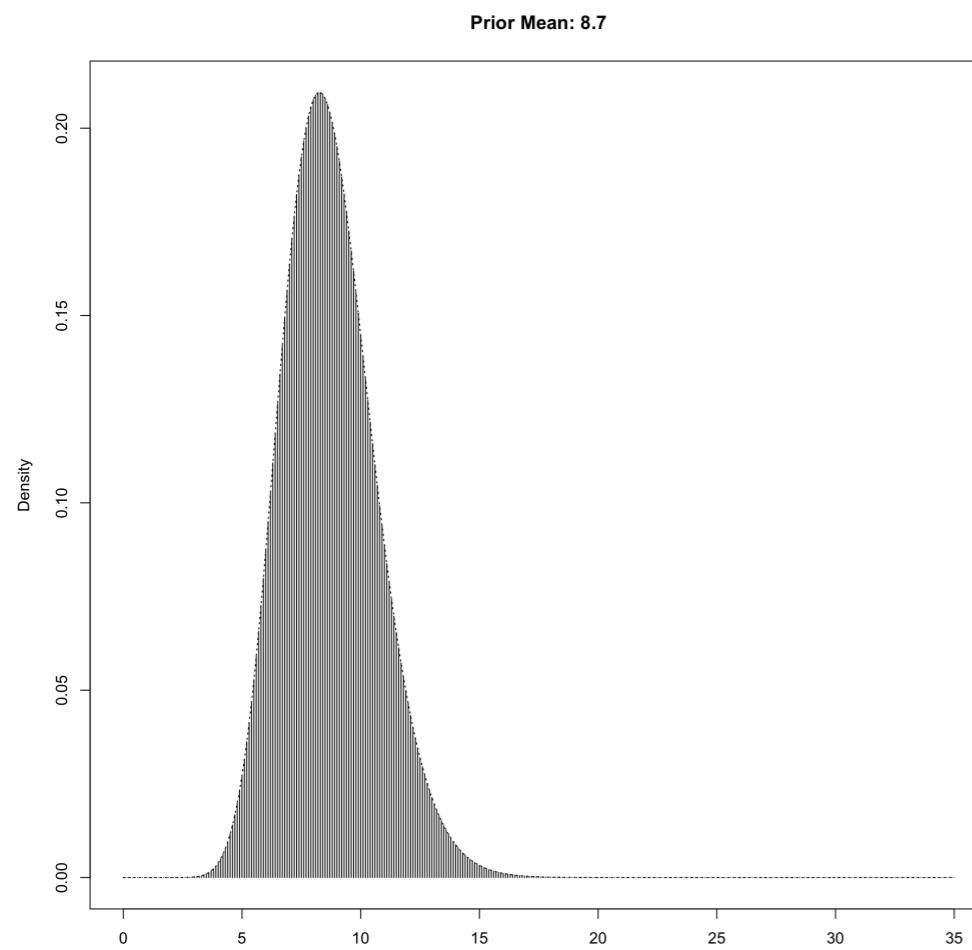


Lambda

$\lambda \sim Gamma(\alpha = 0.1, \beta = 3.3)$

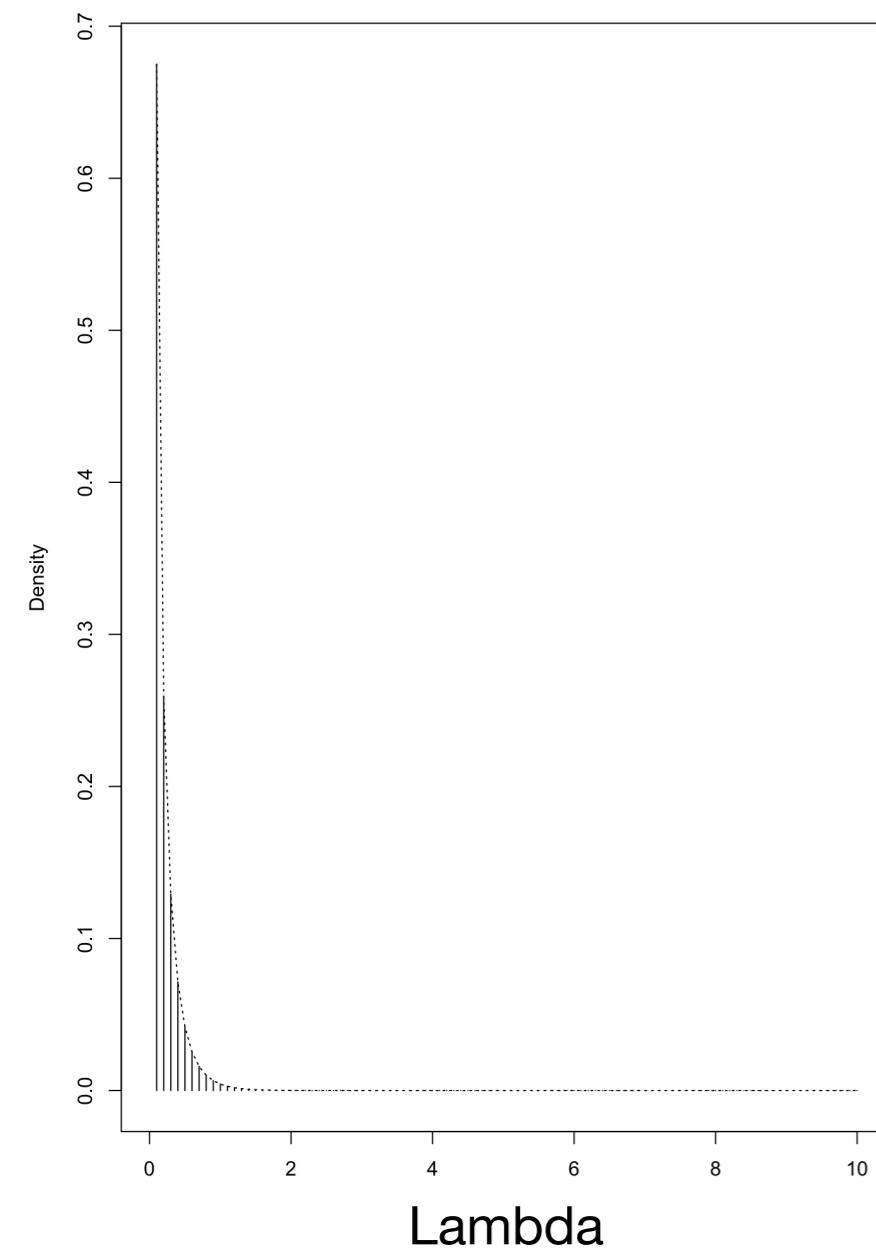
$$\hat{\lambda} = 8.4$$

$\lambda | \mathbf{X} \sim Gamma(\alpha = 0.1 + \sum x_i, \beta = 3.3 + n)$



Prior

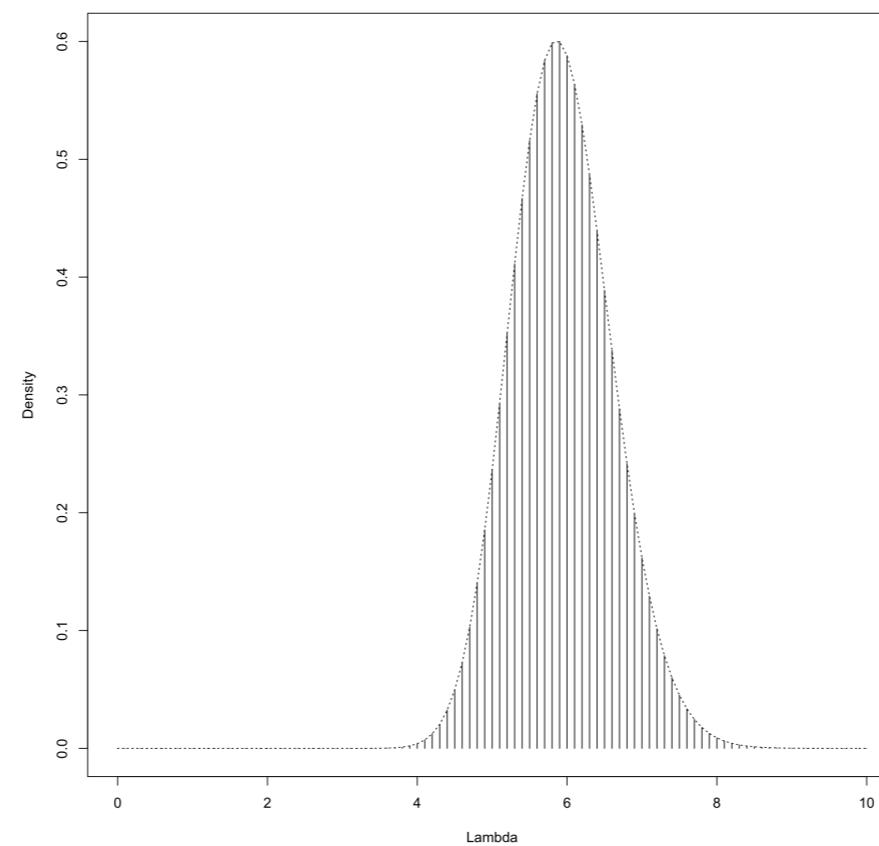
Prior Mean: 0.03



$$\lambda \sim \text{Gamma}(\alpha = 0.1, \beta = 3.3)$$

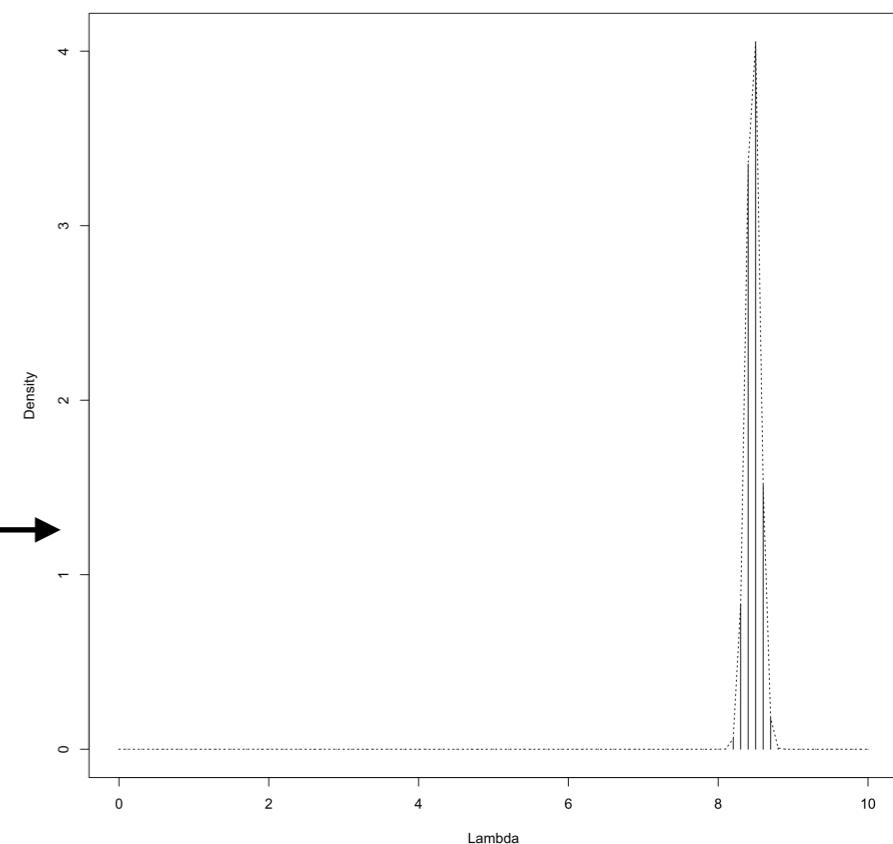
n=3

Posterior Mean: 5.93

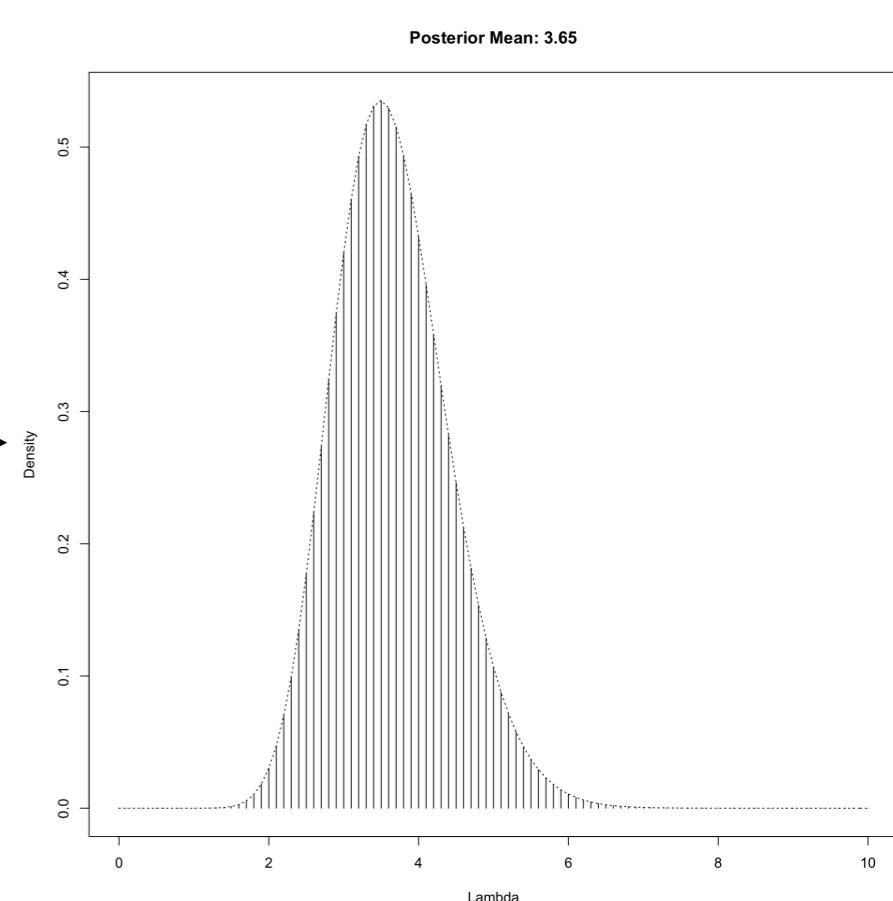


n=1000

Posterior Mean: 8.47



Density



Bayesian: Likelihood 2.0

- Incorporate prior knowledge
- You get a distribution, not just a point estimate

Your knowledge

Prior

Prior Mean: 0.03

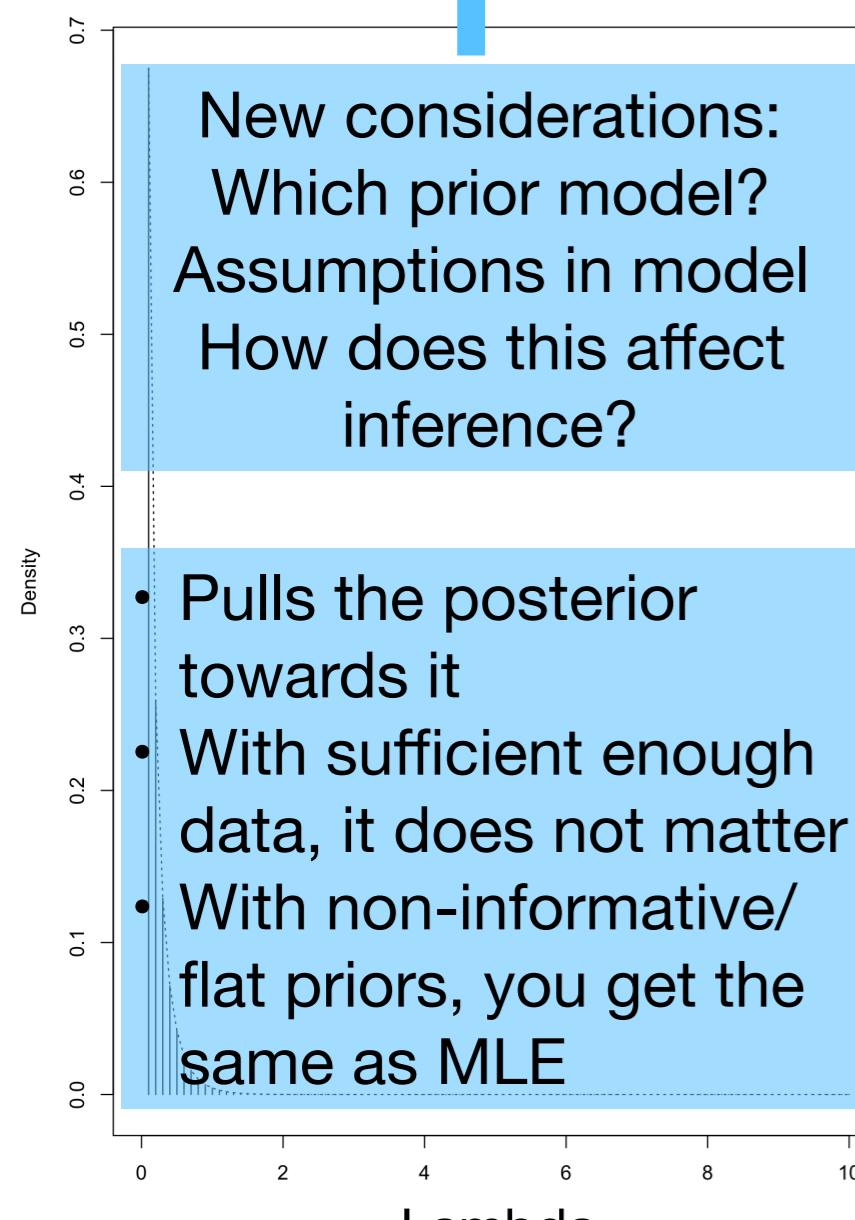
Information in the data

Likelihood

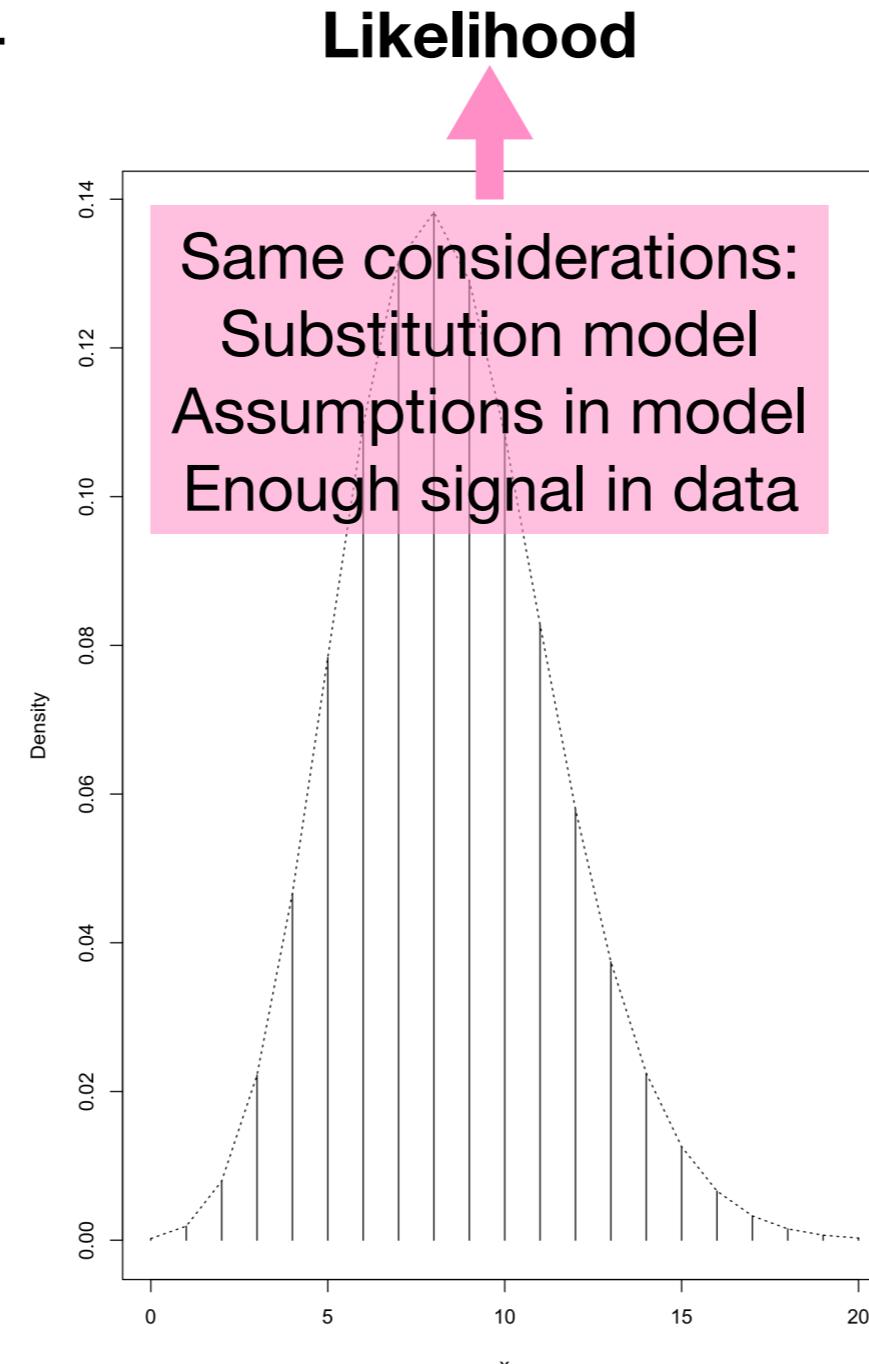
Inference on parameter

Posterior

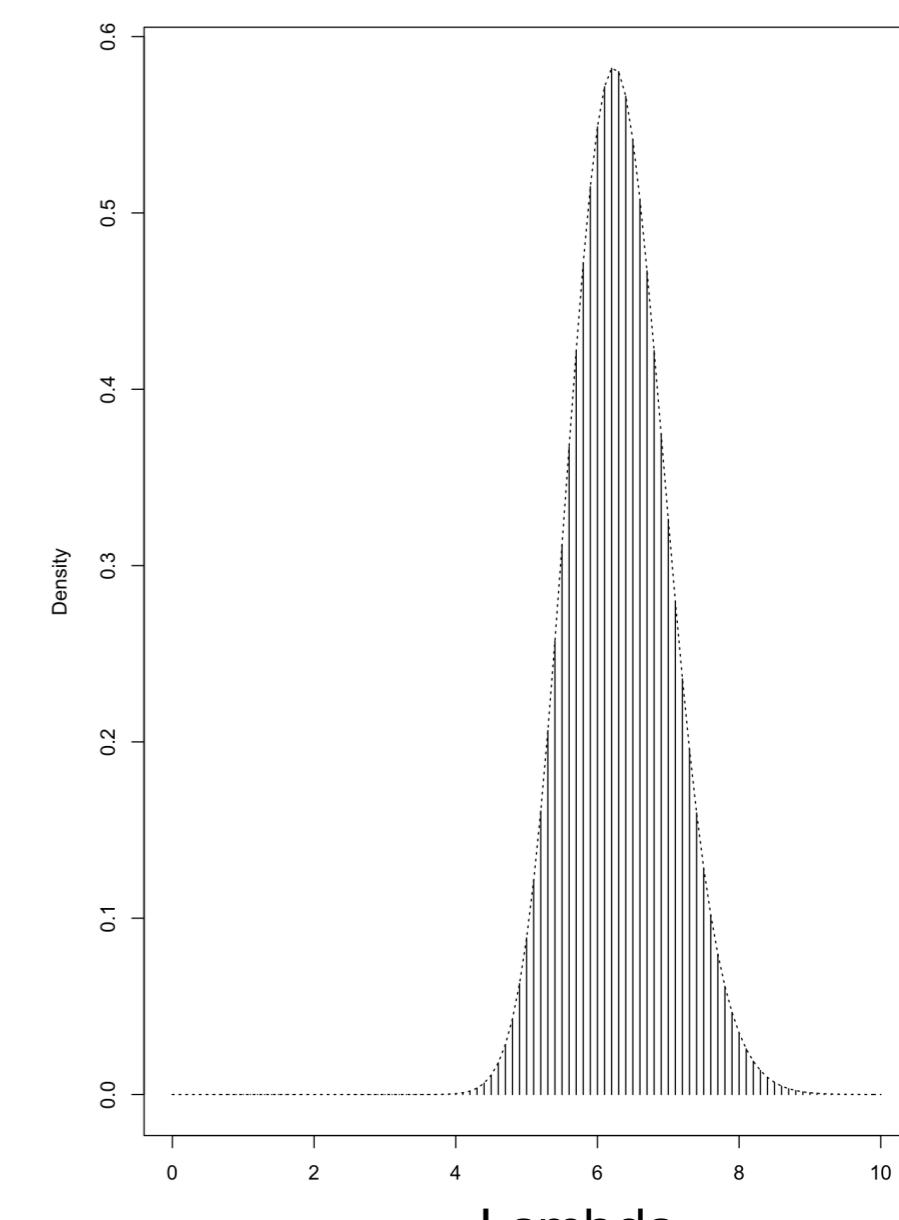
Posterior Mean: 6.31



$$\lambda \sim \text{Gamma}(\alpha = 0.1, \beta = 3.3)$$



$$\hat{\lambda} = 8.4$$



$$\lambda | \mathbf{X} \sim \text{Gamma}(\alpha = 0.1 + \sum x_i, \beta = 3.3 + n)$$

Posterior distribution

$$P(\lambda|\mathbf{X}) = \frac{L_{\mathbf{X}}(\lambda)p(\lambda)}{p(\mathbf{X})} = \frac{\underset{\text{Likelihood}}{\prod P(X = x_i|\lambda)}}{\underset{\text{Marginal}}{p(\mathbf{X})}} \underset{\text{Prior}}{p(\lambda)}$$

← Many times,
intractable

Posterior distribution

$$P(\lambda|\mathbf{X}) = \frac{L_{\mathbf{X}}(\lambda)p(\lambda)}{p(\mathbf{X})} = \frac{\underset{\text{Likelihood}}{\prod P(X = x_i|\lambda)}}{\underset{\text{Marginal}}{p(\mathbf{X})}} \underset{\text{Prior}}{p(\lambda)}$$

← Many times,
intractable

$$\Rightarrow P(\lambda|\mathbf{X}) \propto L_{\mathbf{X}}(\lambda)p(\lambda)$$

Posterior distribution

$$\Rightarrow P(\lambda|\mathbf{X}) \propto L_{\mathbf{X}}(\lambda)p(\lambda)$$

$$X_i|\lambda \sim Poisson(\lambda)$$

$$\lambda \sim Gamma(\alpha, \beta)$$

$$P(\lambda|\mathbf{X}) \propto \left(\prod_{i=1}^n \frac{e^{-\lambda} \lambda^{x_i}}{x_i!} \right) \frac{\beta^\alpha}{\Gamma(\alpha)} \lambda^{\alpha-1} e^{-\beta\lambda}$$

Posterior distribution

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$$\propto \left(\frac{e^{-n\lambda} \lambda^{\sum x_i}}{\prod x_i!} \right) \lambda^{\alpha-1} e^{-\beta\lambda}$$

$$\propto \lambda^{\sum x_i + \alpha - 1} e^{-(n + \beta)\lambda}$$

Posterior distribution

$$\Rightarrow P(\lambda|\mathbf{X}) \propto L_{\mathbf{X}}(\lambda)p(\lambda)$$

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$$\propto \lambda^{\sum x_i + \alpha - 1} e^{-(n+\beta)\lambda} \quad \text{← } Gamma\left(\sum x_i + \alpha, n + \beta\right)$$

Posterior distribution

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$$P(\lambda|\mathbf{X}) = \frac{(n+\beta)^{(\sum x_i + \alpha)}}{\Gamma(\sum x_i + \alpha)} \lambda^{\sum x_i + \alpha - 1} e^{-(n+\beta)\lambda}$$

Posterior distribution

$$\Rightarrow P(\lambda|\mathbf{X}) \propto L_{\mathbf{X}}(\lambda)p(\lambda)$$

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$$\lambda|\mathbf{X} \sim Gamma\left(\sum x_i + \alpha, n + \beta\right)$$

Posterior distribution

$$\Rightarrow P(\lambda|\mathbf{X}) \propto L_{\mathbf{X}}(\lambda)p(\lambda)$$

$$X_i|\lambda \sim Poisson(\lambda)$$

$$\lambda \sim Gamma(\alpha, \beta) \quad \text{Conjugate prior}$$

$$P(\lambda|\mathbf{X}) \propto \left(\prod_{i=1}^n \frac{e^{-\lambda} \lambda^{x_i}}{x_i!} \right) \frac{\beta^\alpha}{\Gamma(\alpha)} \lambda^{\alpha-1} e^{-\beta\lambda}$$

$$P(\lambda|\mathbf{X}) = \frac{(n+\beta)^{(\sum x_i + \alpha)}}{\Gamma(\sum x_i + \alpha)} \lambda^{\sum x_i + \alpha - 1} e^{-(n+\beta)\lambda}$$

$$\lambda|\mathbf{X} \sim Gamma \left(\sum x_i + \alpha, n + \beta \right)$$

Posterior distribution

$$\Rightarrow P(\lambda|\mathbf{X}) \propto L_{\mathbf{X}}(\lambda)p(\lambda)$$

$$X_i|\lambda \sim Poisson(\lambda)$$

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$$P(\lambda|\mathbf{X}) = \frac{(n+\beta)^{(\sum x_i + \alpha)}}{\Gamma(\sum x_i + \alpha)} \lambda^{\sum x_i + \alpha - 1} e^{-(n+\beta)\lambda}$$

$$\lambda|\mathbf{X} \sim Gamma\left(\sum x_i + \alpha, n + \beta\right)$$

Posterior mean: $\frac{\sum x_i + \alpha}{n + \beta} = \frac{n}{n + \beta} \left(\frac{\sum x_i}{n} \right) + \frac{\beta}{n + \beta} \left(\frac{\alpha}{\beta} \right)$

Intractable posterior distribution

$$X_i | \lambda \sim Poisson(\lambda)$$

$$\lambda \sim Lognormal(\mu, \sigma)$$

$$P(\lambda | \mathbf{X}) \propto \left(\prod_{i=1}^n \frac{e^{-\lambda} \lambda^{x_i}}{x_i!} \right) \frac{1}{\lambda \sigma \sqrt{2\pi}} \exp \left(-\frac{(\log \lambda - \mu)^2}{2\sigma^2} \right)$$

Intractable posterior distribution

$$X_i | \lambda \sim Poisson(\lambda)$$

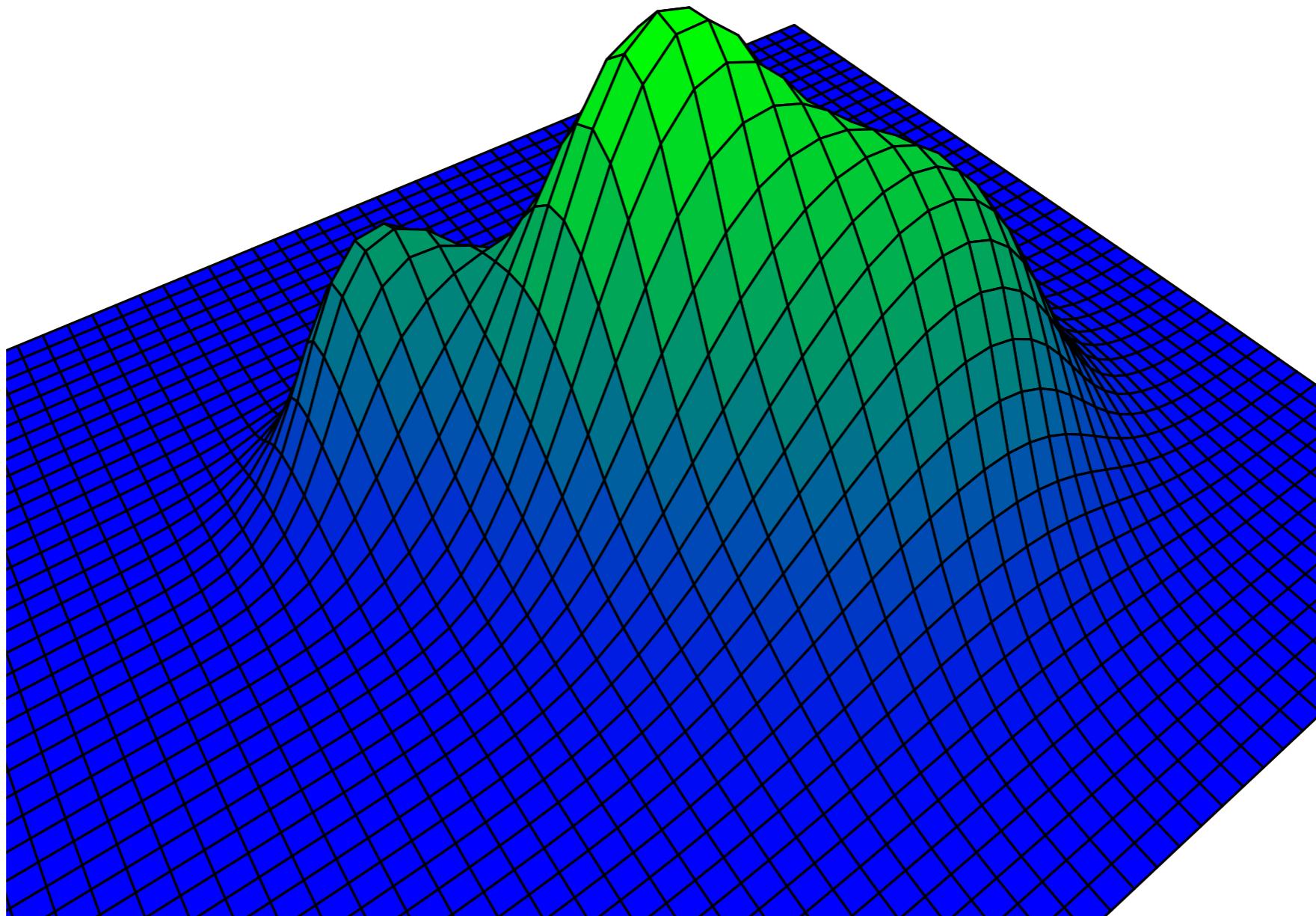
$$\lambda \sim Lognormal(\mu, \sigma)$$

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**Not a known
distribution anymore
We need to
approximate it**

MCMC: A way to approximate intractable posterior distributions



MCMC: A way to approximate intractable posterior distributions

$$P(\lambda|\mathbf{X}) \propto \left(\prod_{i=1}^n \frac{e^{-\lambda} \lambda^{x_i}}{x_i!} \right) \frac{1}{\lambda \sigma \sqrt{2\pi}} \exp\left(-\frac{(\log \lambda - \mu)^2}{2\sigma^2}\right)$$

Initialization: Start at a random λ_0

Loop: For i , propose a new lambda

$$\lambda^* \sim Uniform(\lambda_{i-1} - w/2, \lambda_{i-1} + w/2)$$

- If $P(\lambda^*|\mathbf{X}) > P(\lambda_{i-1}|\mathbf{X}) \Rightarrow \lambda_i = \lambda^*$

- Else, accept $\lambda_i = \lambda^*$ with probability
- Otherwise, $\lambda_i = \lambda_{i-1}$

$$\alpha = \frac{P(\lambda^*|\mathbf{X})}{P(\lambda_{i-1}|\mathbf{X})}$$

MCMC: A way to approximate intractable posterior distributions

$$P(\lambda|\mathbf{X}) \propto \left(\prod_{i=1}^n \frac{e^{-\lambda} \lambda^{x_i}}{x_i!} \right) \frac{1}{\lambda \sigma \sqrt{2\pi}} \exp\left(-\frac{(\log \lambda - \mu)^2}{2\sigma^2}\right)$$

Initialization: Start at a random λ_0

Loop: For i , propose a new lambda

$$\lambda^* \sim \text{Uniform}(\lambda_{i-1} - w/2, \lambda_{i-1} + w/2)$$

- If $P(\lambda^*|\mathbf{X}) > P(\lambda_{i-1}|\mathbf{X}) \Rightarrow \lambda_i = \lambda^*$

$$\alpha = \frac{P(\lambda^*|\mathbf{X})}{P(\lambda_{i-1}|\mathbf{X})}$$

- Else, accept $\lambda_i = \lambda^*$ with probability α
- Otherwise, $\lambda_i = \lambda_{i-1}$

Proposal distribution

Usually symmetric,
but could be
asymmetric
(Hasting ratio)

MCMC: A way to approximate intractable posterior distributions

$$P(\lambda|\mathbf{X}) \propto \left(\prod_{i=1}^n \frac{e^{-\lambda} \lambda^{x_i}}{x_i!} \right) \frac{1}{\lambda \sigma \sqrt{2\pi}} \exp\left(-\frac{(\log \lambda - \mu)^2}{2\sigma^2}\right)$$

Initialization: Start at a random λ_0

Loop: For i , propose a new lambda

$$\lambda^* \sim \text{Uniform}(\lambda_{i-1} - w/2, \lambda_{i-1} + w/2)$$

- If $P(\lambda^*|\mathbf{X}) > P(\lambda_{i-1}|\mathbf{X}) \Rightarrow \lambda_i = \lambda^*$

$$\alpha = \frac{P(\lambda^*|\mathbf{X})}{P(\lambda_{i-1}|\mathbf{X})}$$

- Else, accept $\lambda_i = \lambda^*$ with probability α
- Otherwise, $\lambda_i = \lambda_{i-1}$

Proposal distribution

Usually symmetric,
but could be
asymmetric
(Hasting ratio)

Acceptance probability

Posterior ratio

MCMC: A way to approximate intractable posterior distributions

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Proposal distribution

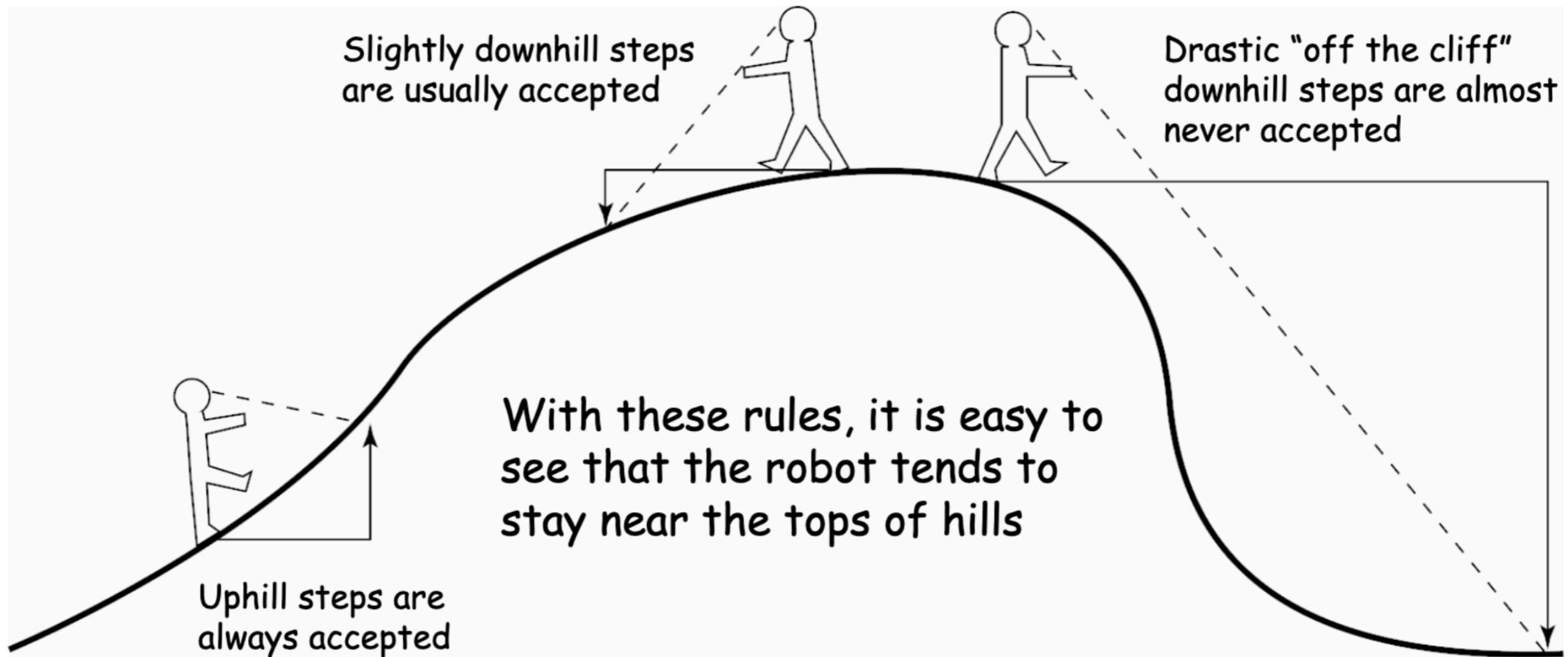
Usually symmetric,
but could be
asymmetric
(Hasting ratio)

Acceptance probability

Posterior ratio

The chain tends to stay on regions of high posterior

MCMC robot's rules



Hastings ratio

$$\alpha = \left[\frac{P(\lambda^* | \mathbf{X})}{P(\lambda | \mathbf{X})} \right] \left[\frac{q(\lambda | \lambda^*)}{q(\lambda^* | \lambda)} \right]$$

Proposal distribution

Posterior ratio

Hastings ratio

MCMC: A way to approximate intractable posterior distributions

$$P(\lambda|\mathbf{X}) \propto \left(\prod_{i=1}^n \frac{e^{-\lambda} \lambda^{x_i}}{x_i!} \right) \frac{1}{\lambda \sigma \sqrt{2\pi}} \exp\left(-\frac{(\log \lambda - \mu)^2}{2\sigma^2}\right)$$

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- Else, accept $\lambda_i = \lambda^*$ with probability

- Otherwise, $\lambda_i = \lambda_{i-1}$

Optional (highly recommended) homework:

- Code the MCMC for this example in your preferred programming language
- Plot the MCMC histogram and compute the posterior mean for lambda
- Play with different values for w and n (length of the chain)

MCMC considerations

- Choice of priors
- Mixing
- Convergence
- Burnin

MCMC considerations

- Choice of priors
- Mixing ← How well you navigate the parameter space?
- Convergence
- Burnin

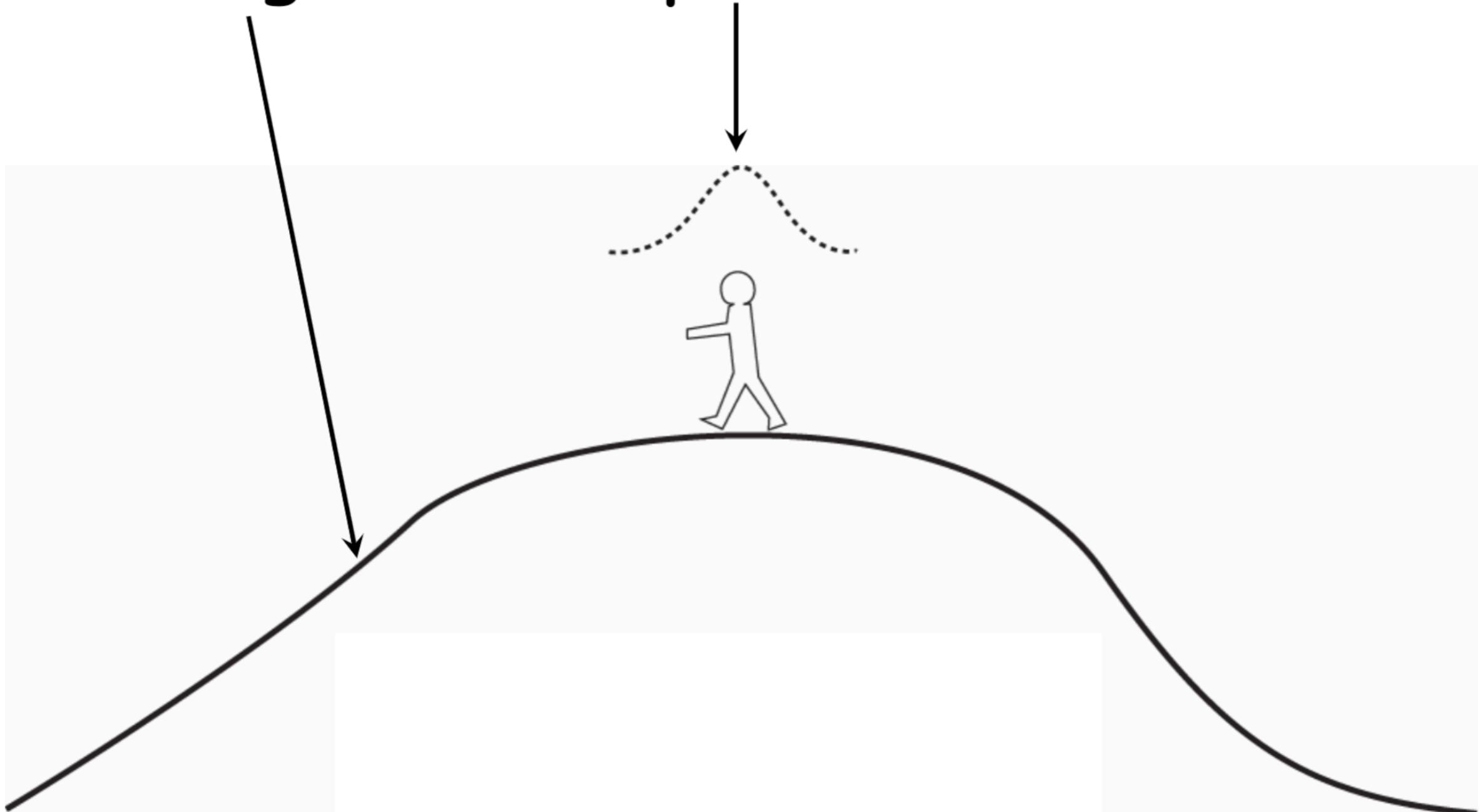
MCMC considerations

- Choice of priors
- Mixing ← How well you navigate the parameter space?
- Convergence ← How well you reach all regions of high posterior values?
- Burnin

MCMC considerations

- Choice of priors
- Mixing ← How well you navigate the parameter space?
- Convergence ← How well you reach all regions of high posterior values?
- Burnin ← How long it takes to reach regions of high posterior values?

Target vs. Proposal Distributions



Target vs. Proposal Distributions

Proposal distributions
with **smaller variance**...



Disadvantage: robot takes
smaller steps, more time
required to explore the
same area

Advantage: robot seldom
refuses to take proposed
steps

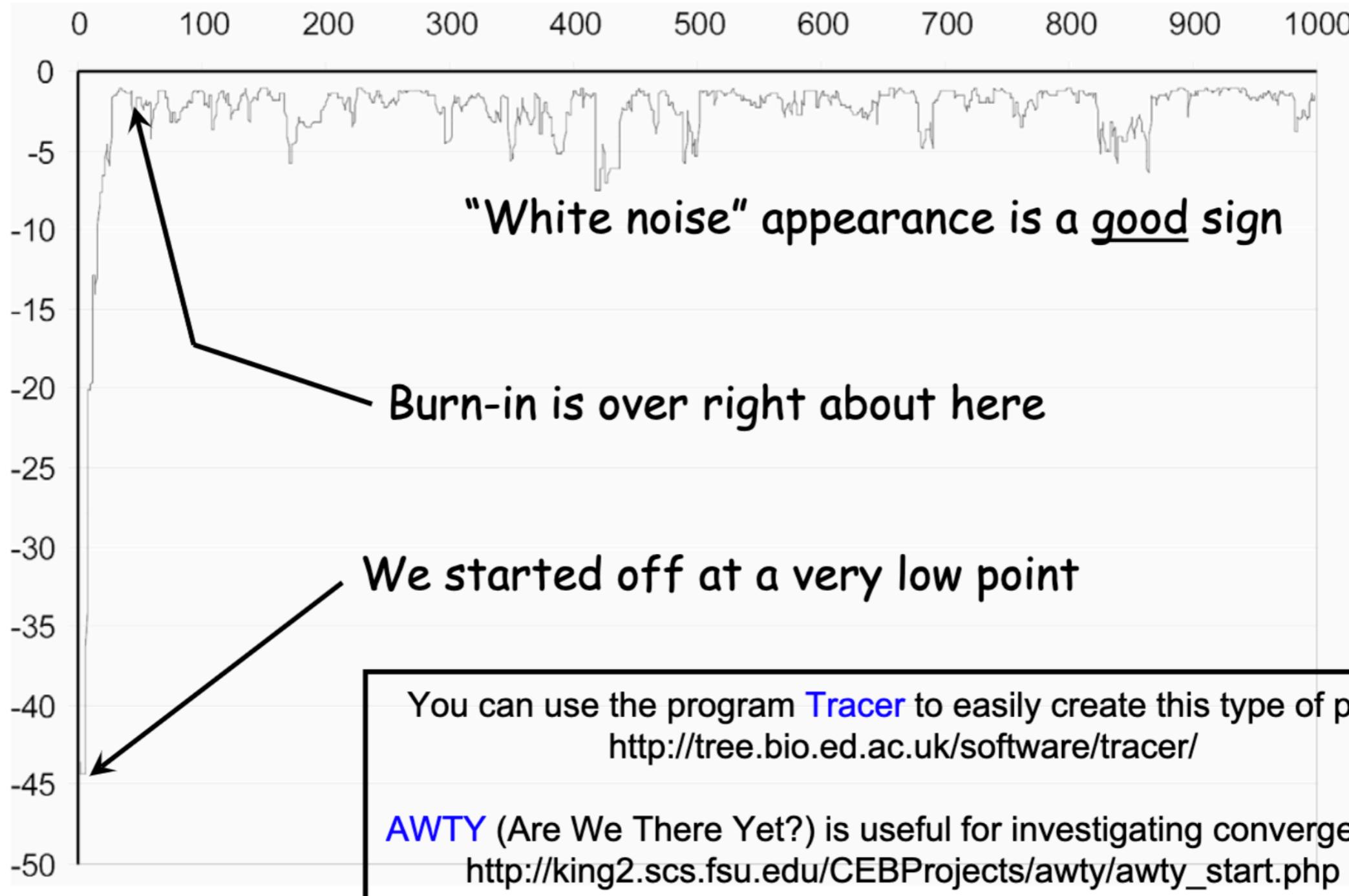
Target vs. Proposal Distributions

Proposal distributions
with **larger variance**...

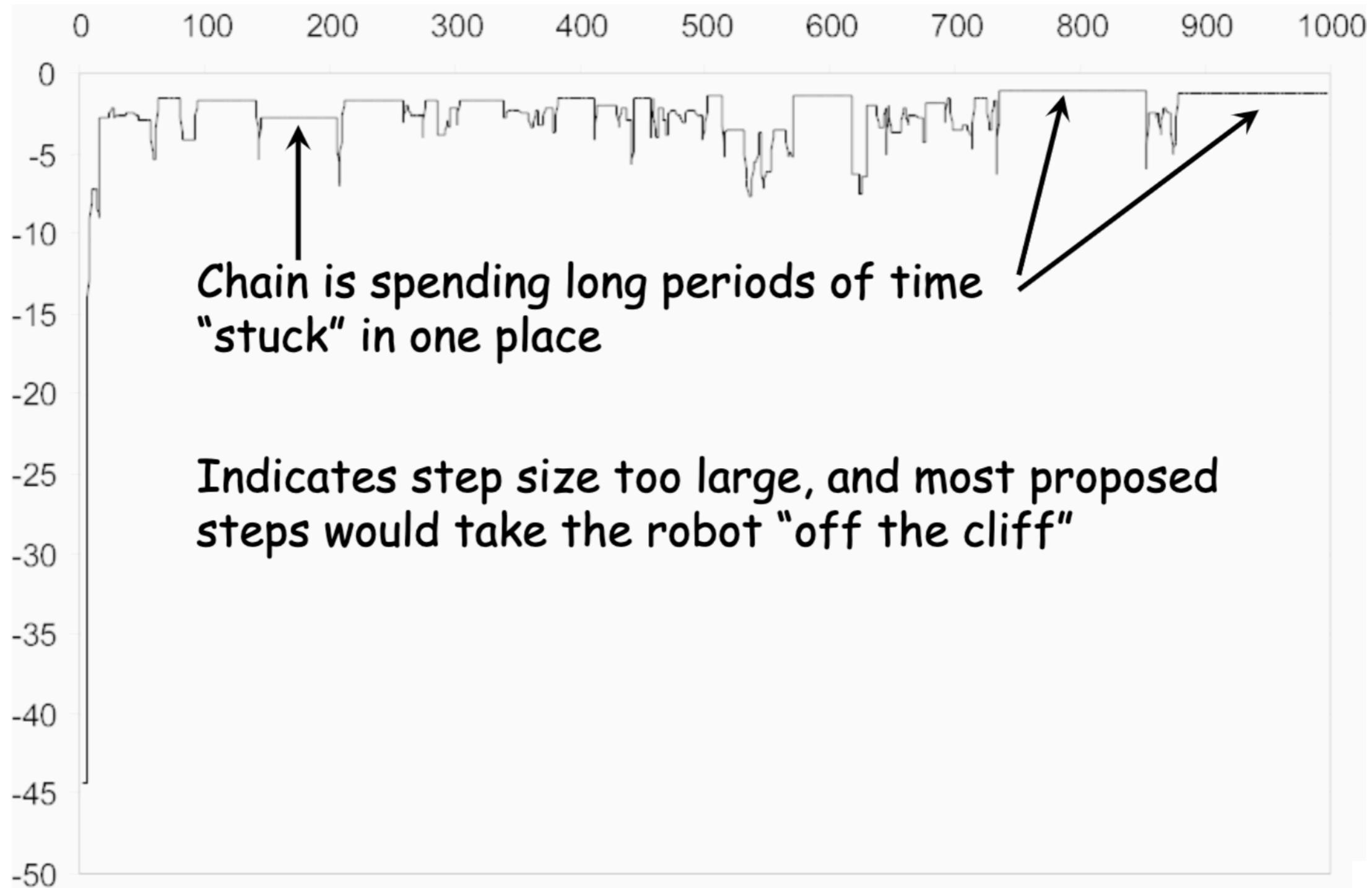
Disadvantage: robot
often proposes a step
that would take it off
a cliff, and refuses to
move



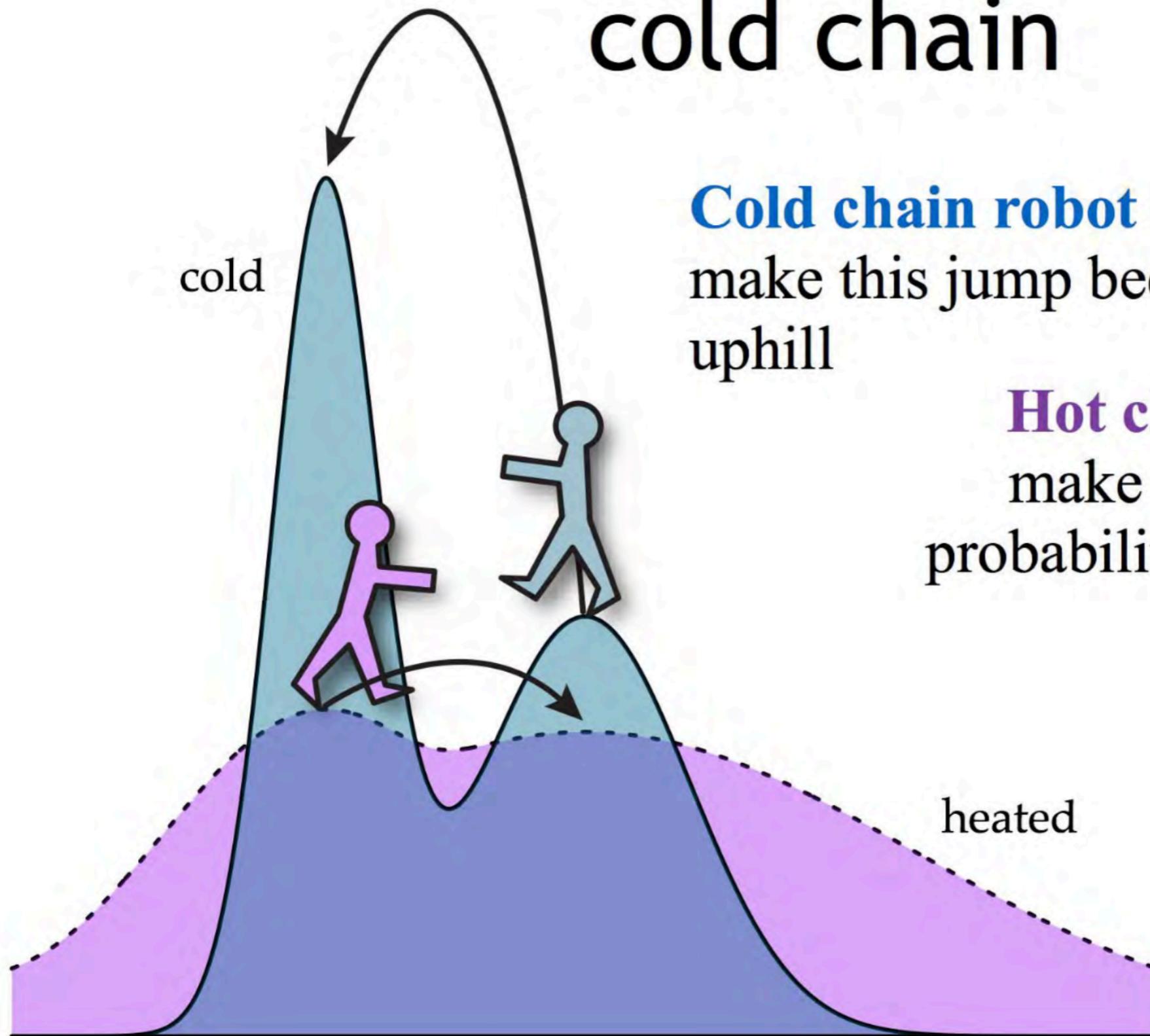
Trace plots



Poor mixing



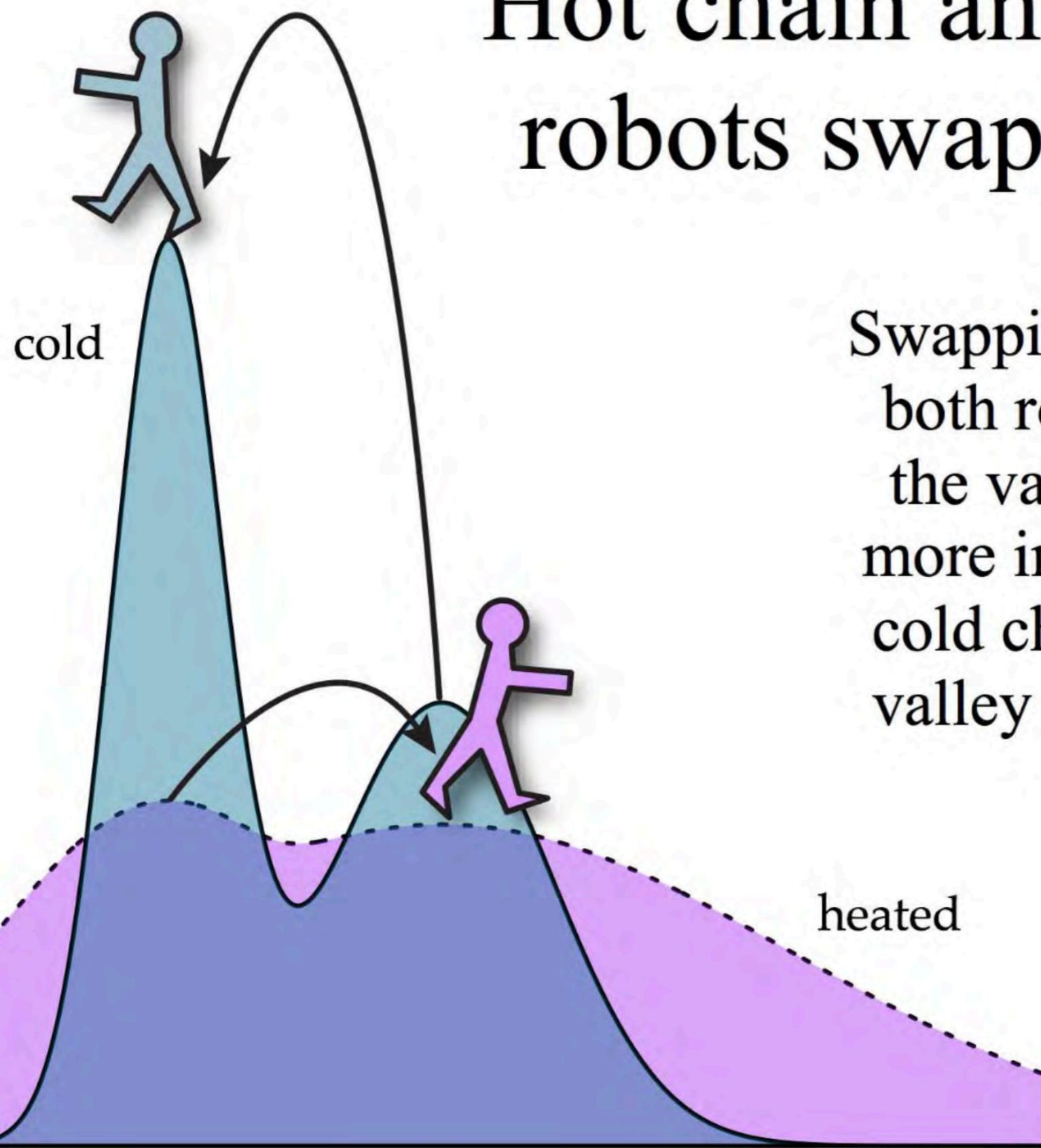
Heated chains act as scouts for the cold chain



Cold chain robot can easily make this jump because it is uphill

Hot chain robot can also make this jump with high probability because it is only slightly downhill

Hot chain and cold chain robots swapping places



Swapping places means both robots can cross the valley, but this is more important for the cold chain because its valley is much deeper

“Metropolis algorithm will produce a precise and accurate approximation of the posterior distribution if run long enough”. - Paul Lewis

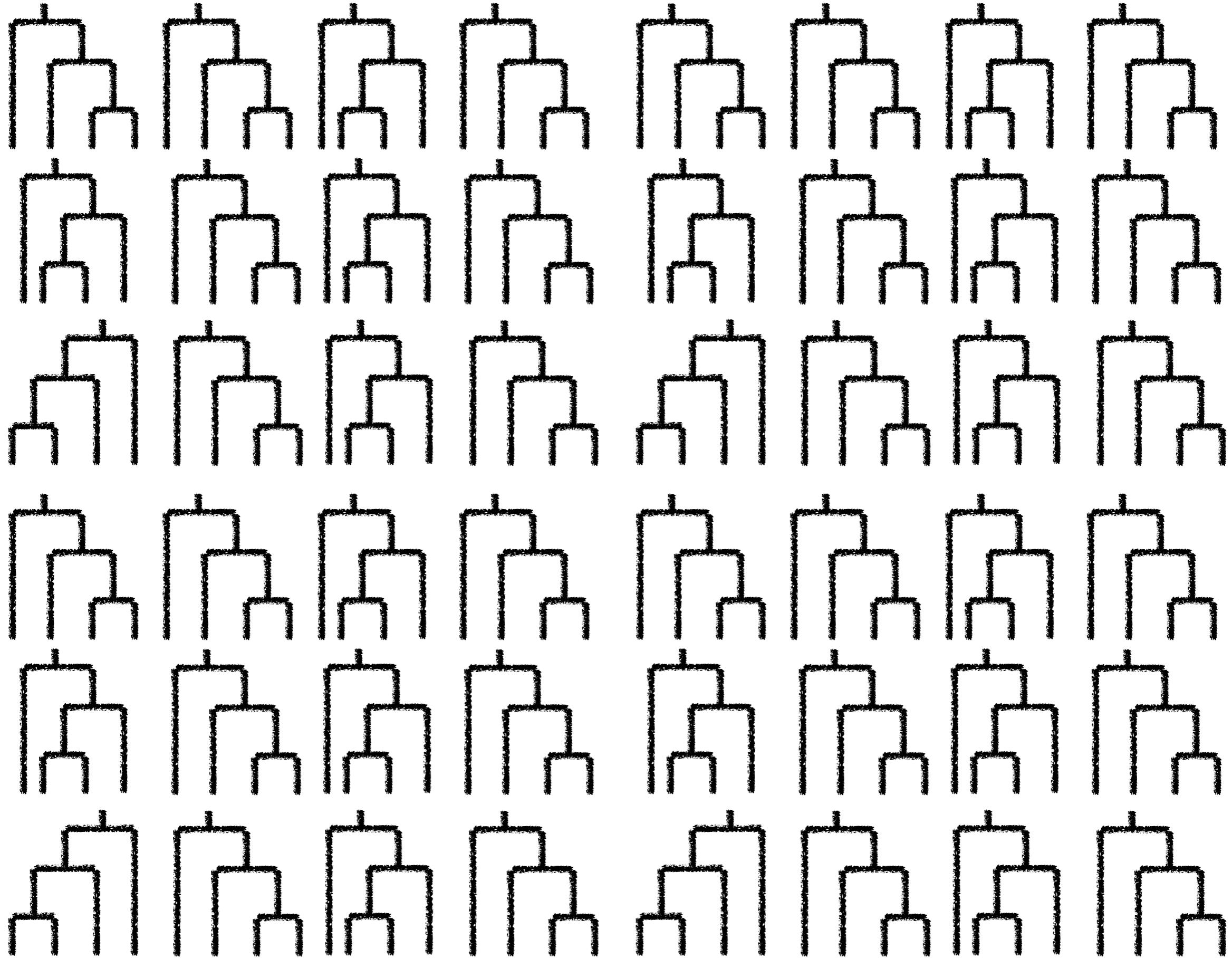
“People always forget how long of a time infinity really is” - paraphrased from Dave Swofford

**Back to
phylogenetics**

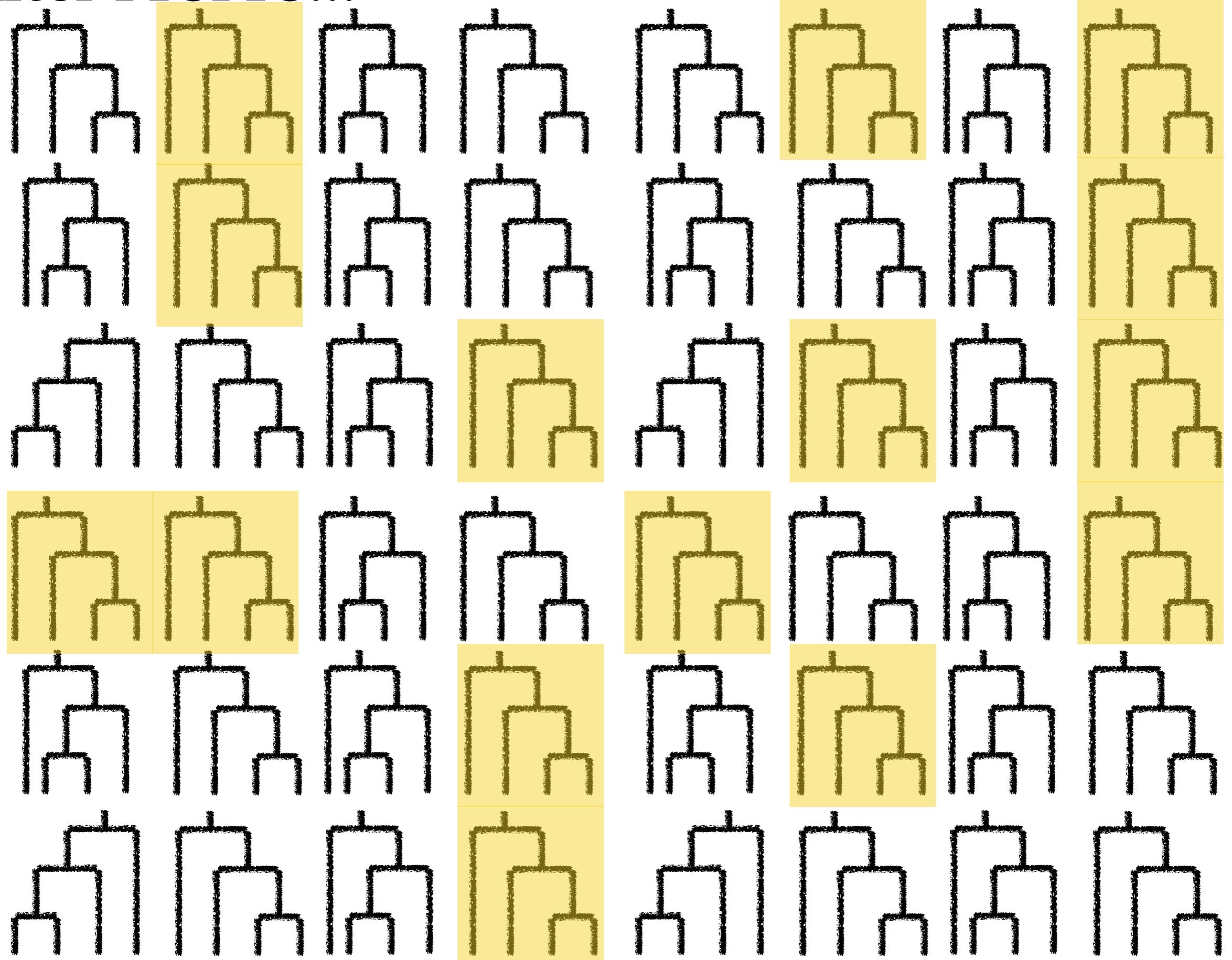
- **Start with** random tree and arbitrary initial values for branch lengths and model parameters
- **Each generation** consists of one of these (chosen at random):
 - Propose a **new tree** (e.g. Larget-Simon move) and either accept or reject the move
 - Propose (and either accept or reject) a **new model parameter value**
- Every k generations, save tree topology, branch lengths and all model parameters (i.e. **sample the chain**)
- After n generations, **summarize sample** using histograms, means, credible intervals, etc.

After MCMC...

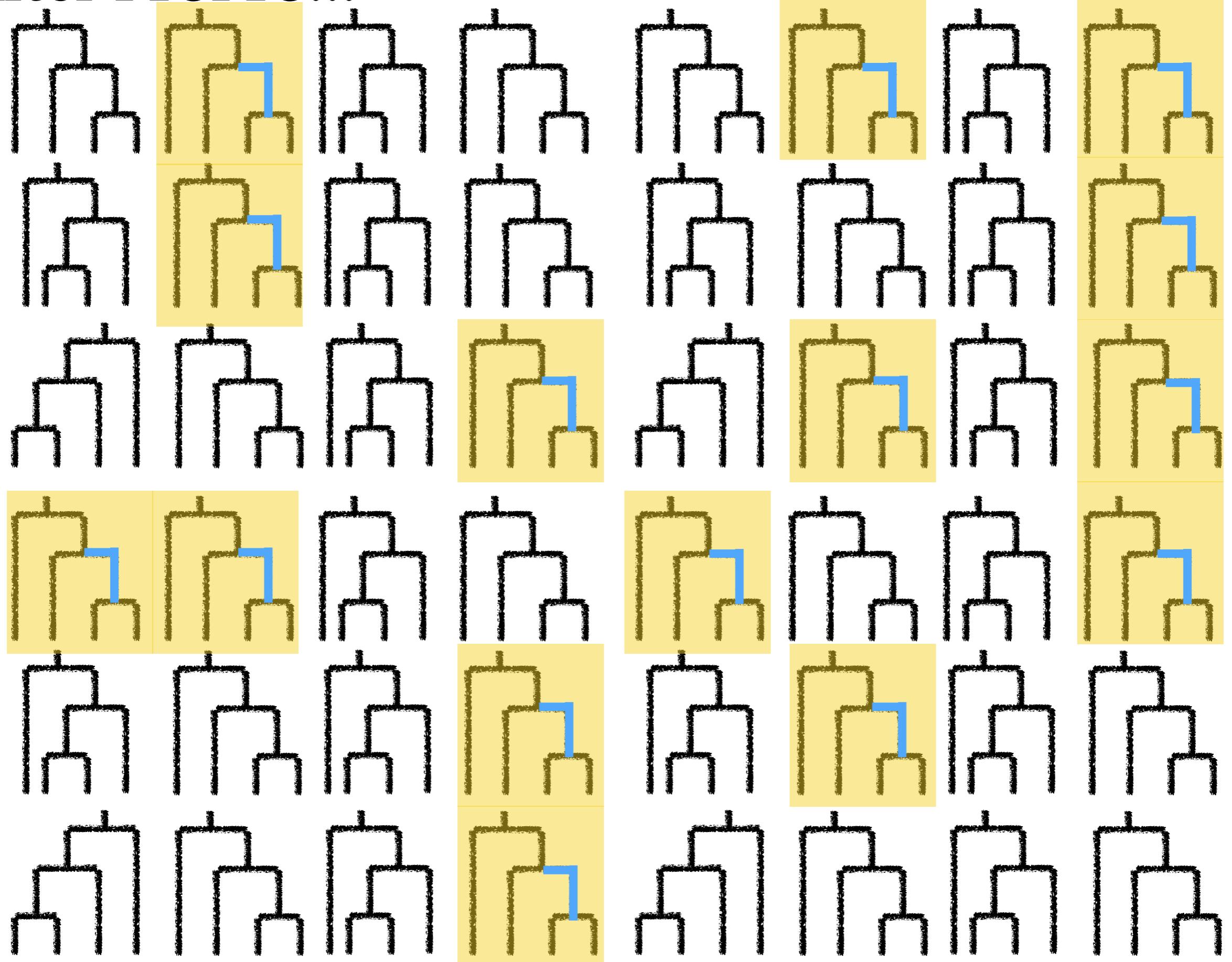
After MCMC...

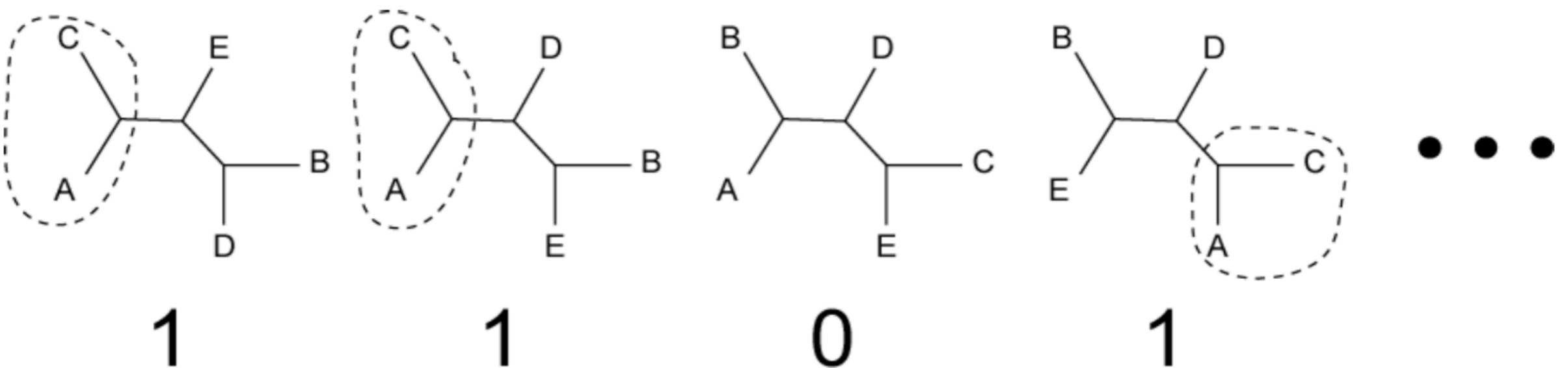


After MCMC...



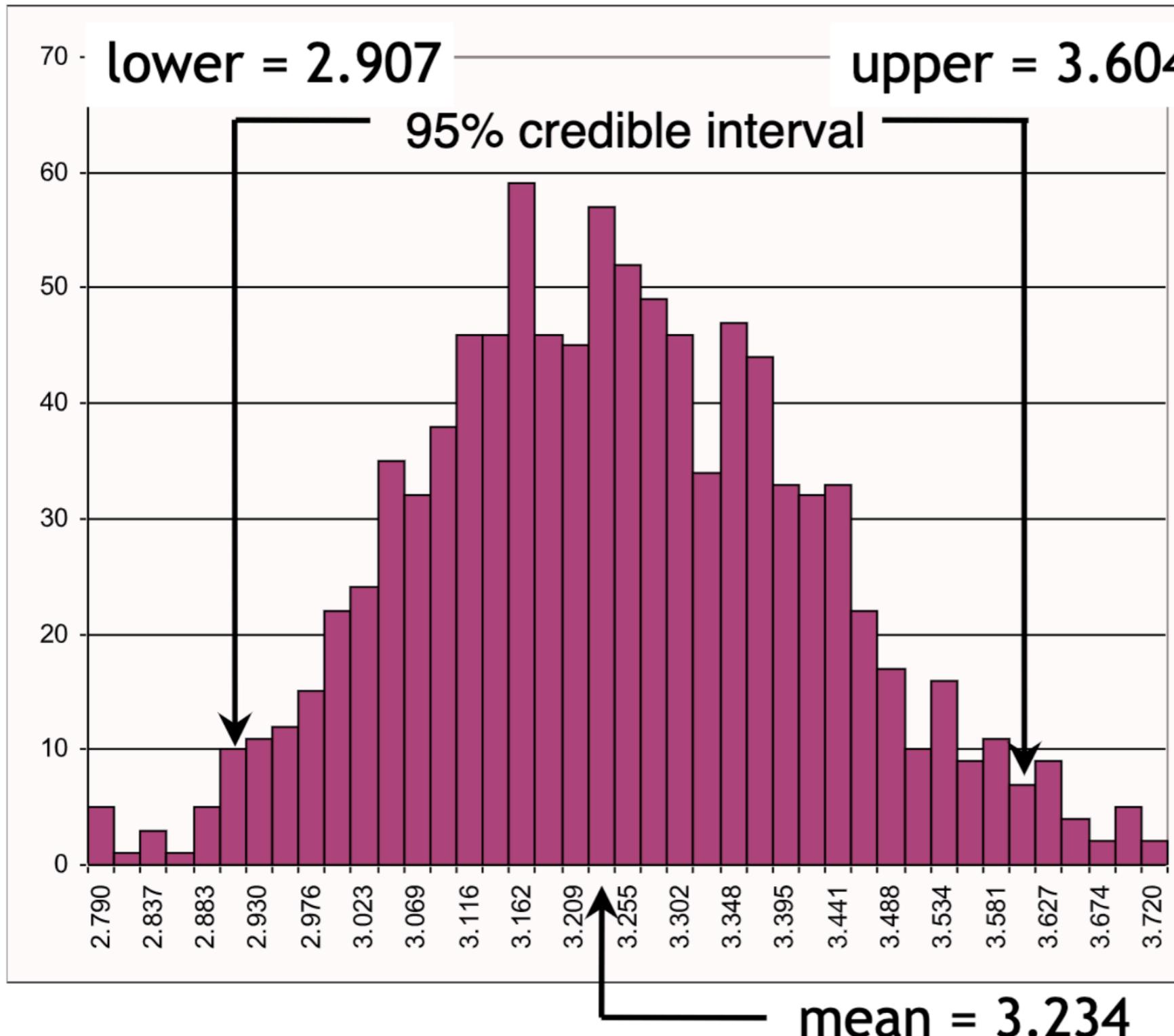
After MCMC...





The posterior probability of the split $AC \mid BDE$ may be approximated by the fraction of trees sampled from the posterior that contain that split.

Marginal Posterior Distribution of κ

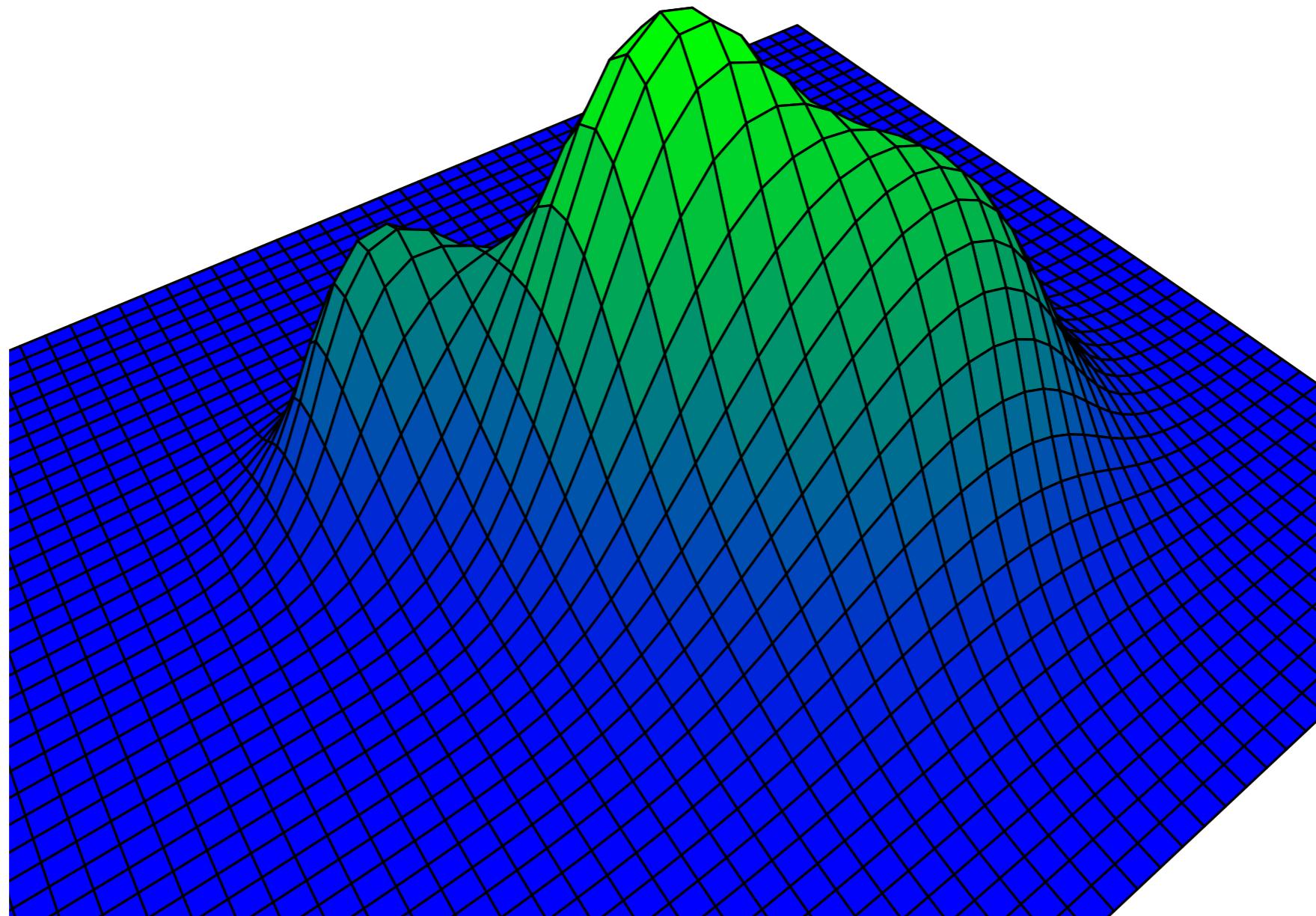


Histogram created from a sample of 1000 kappa values.

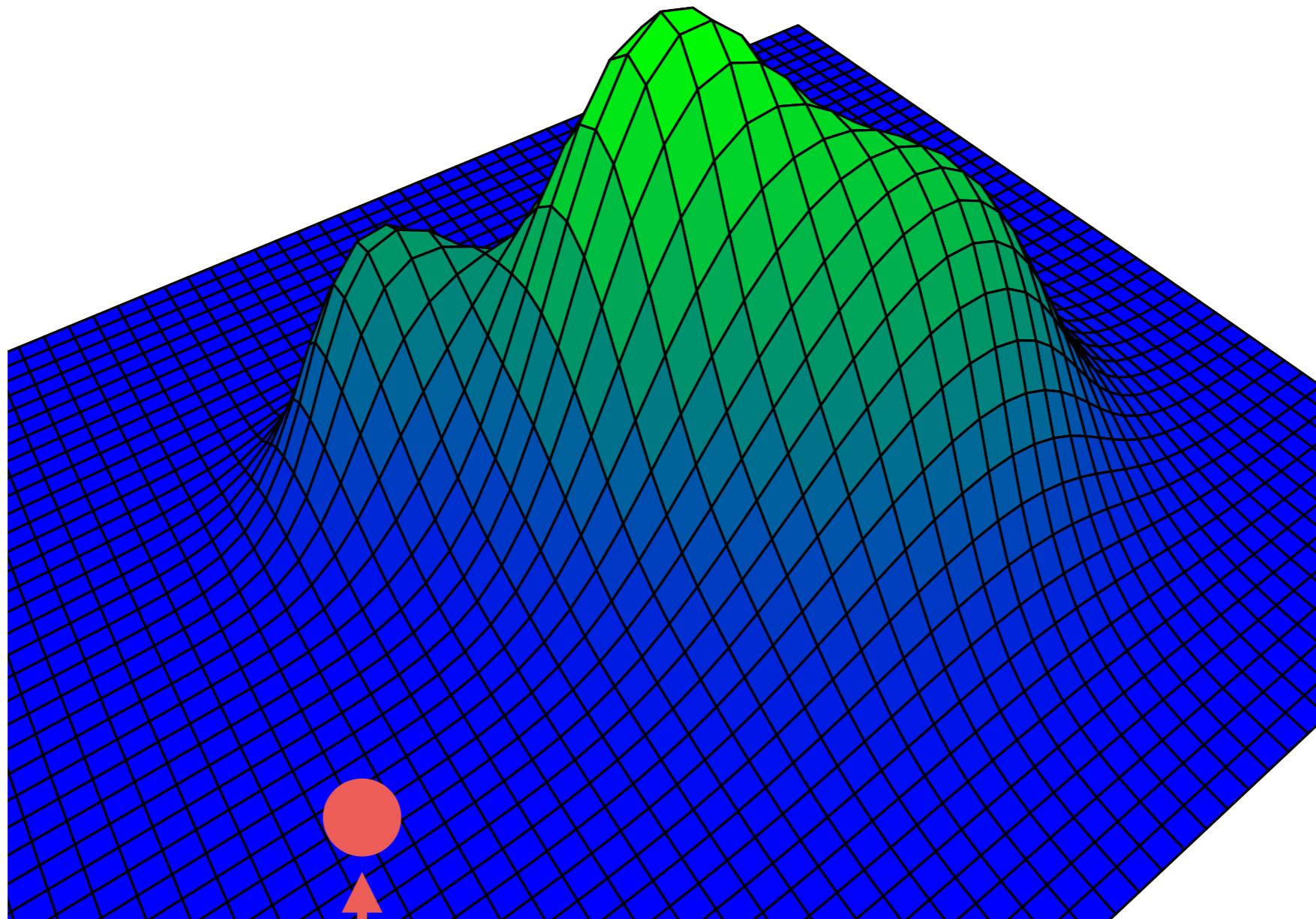
Why is MCMC so slow?

Why is MCMC so slow? Traverse tree space

Why is MCMC so slow? Traverse tree space

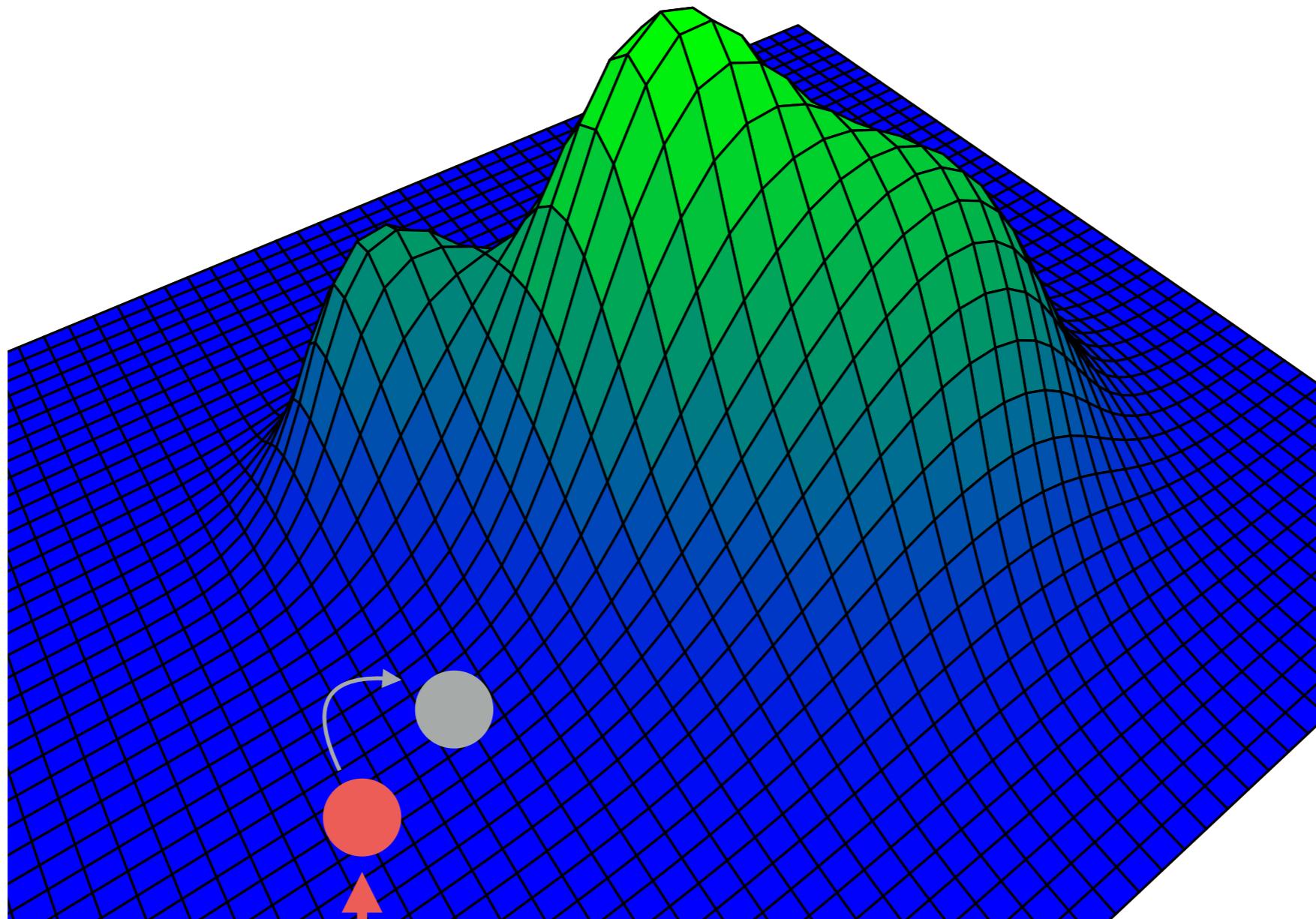


Why is MCMC so slow? Traverse tree space



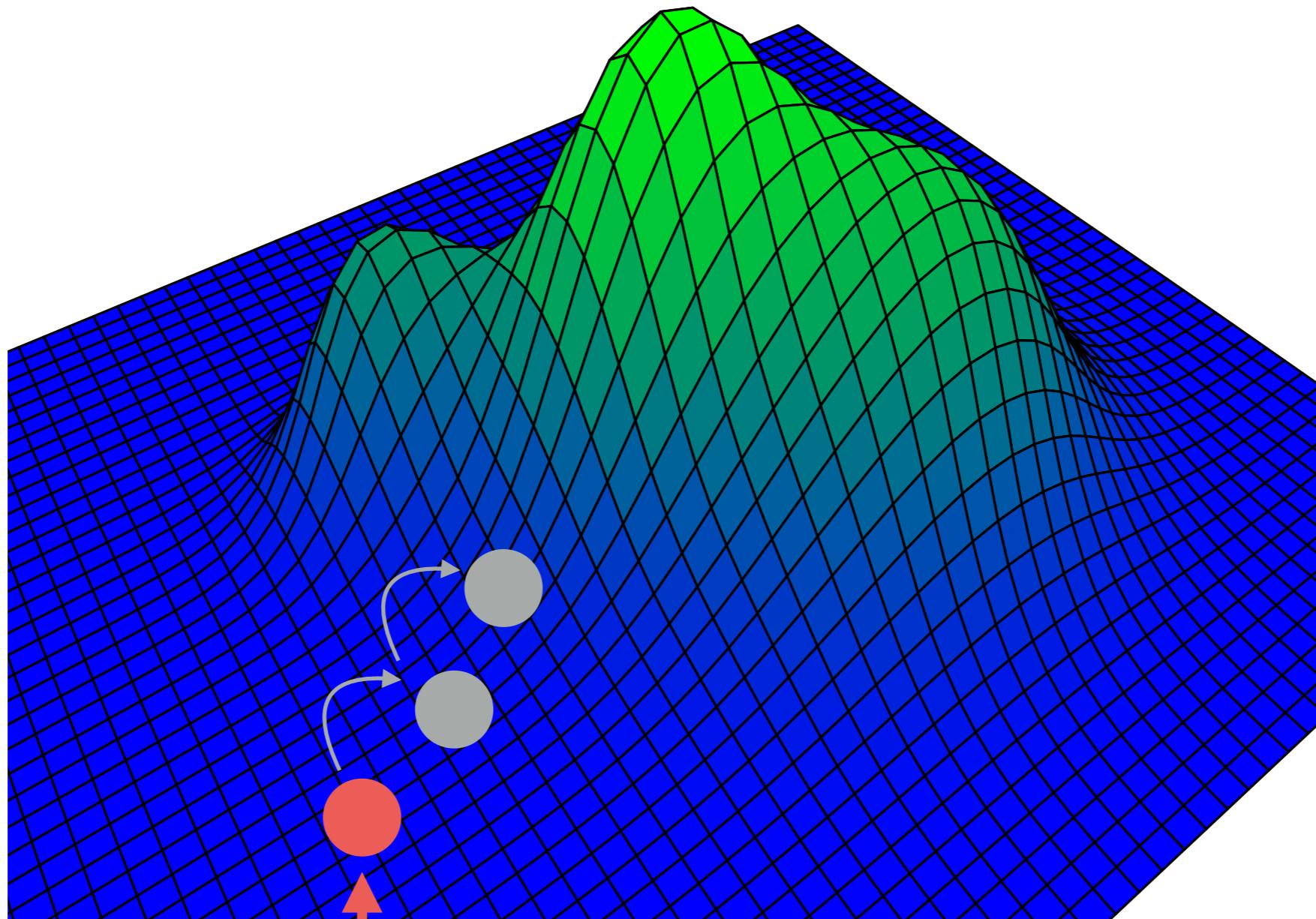
Starting tree

Why is MCMC so slow? Traverse tree space



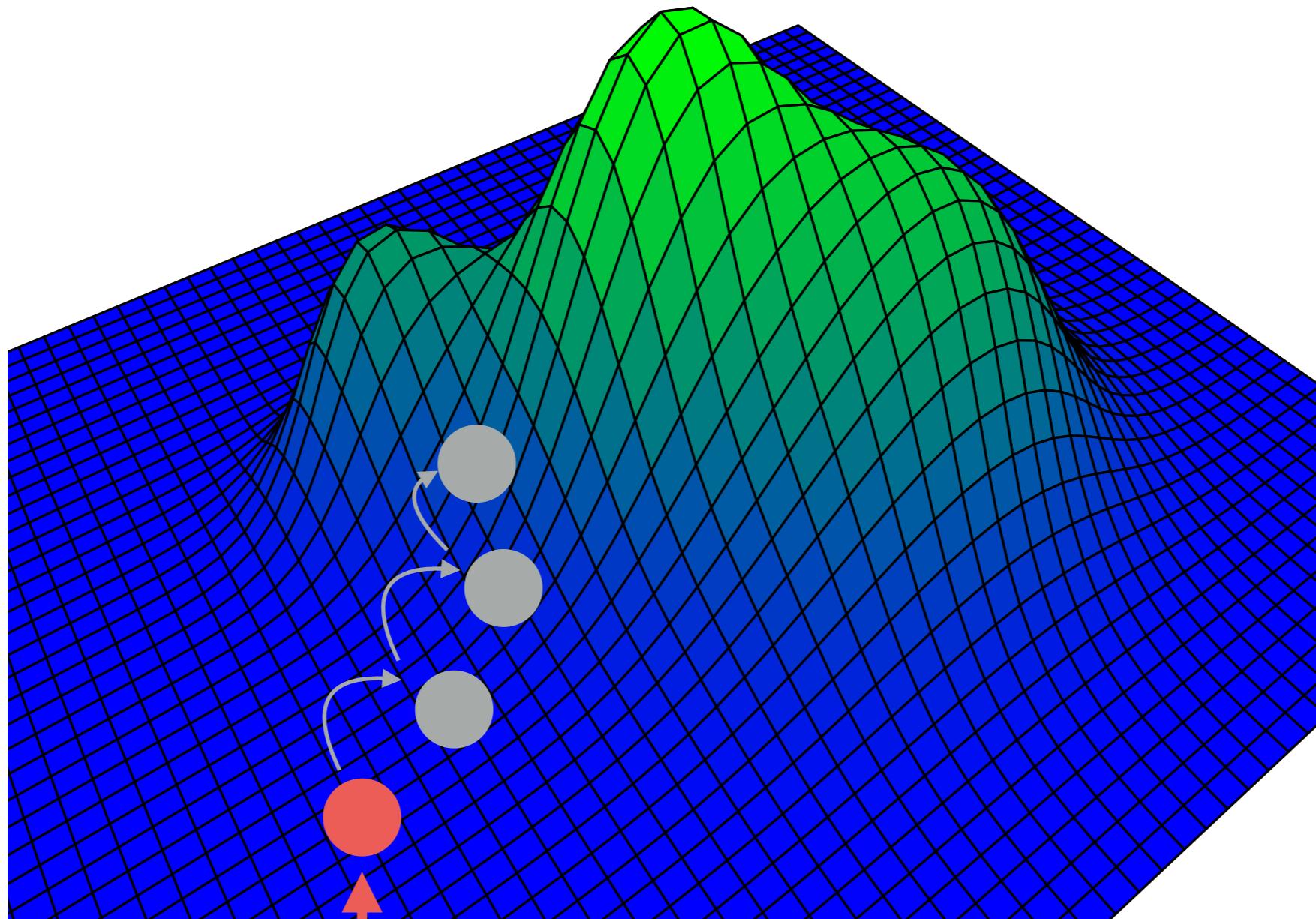
Starting tree

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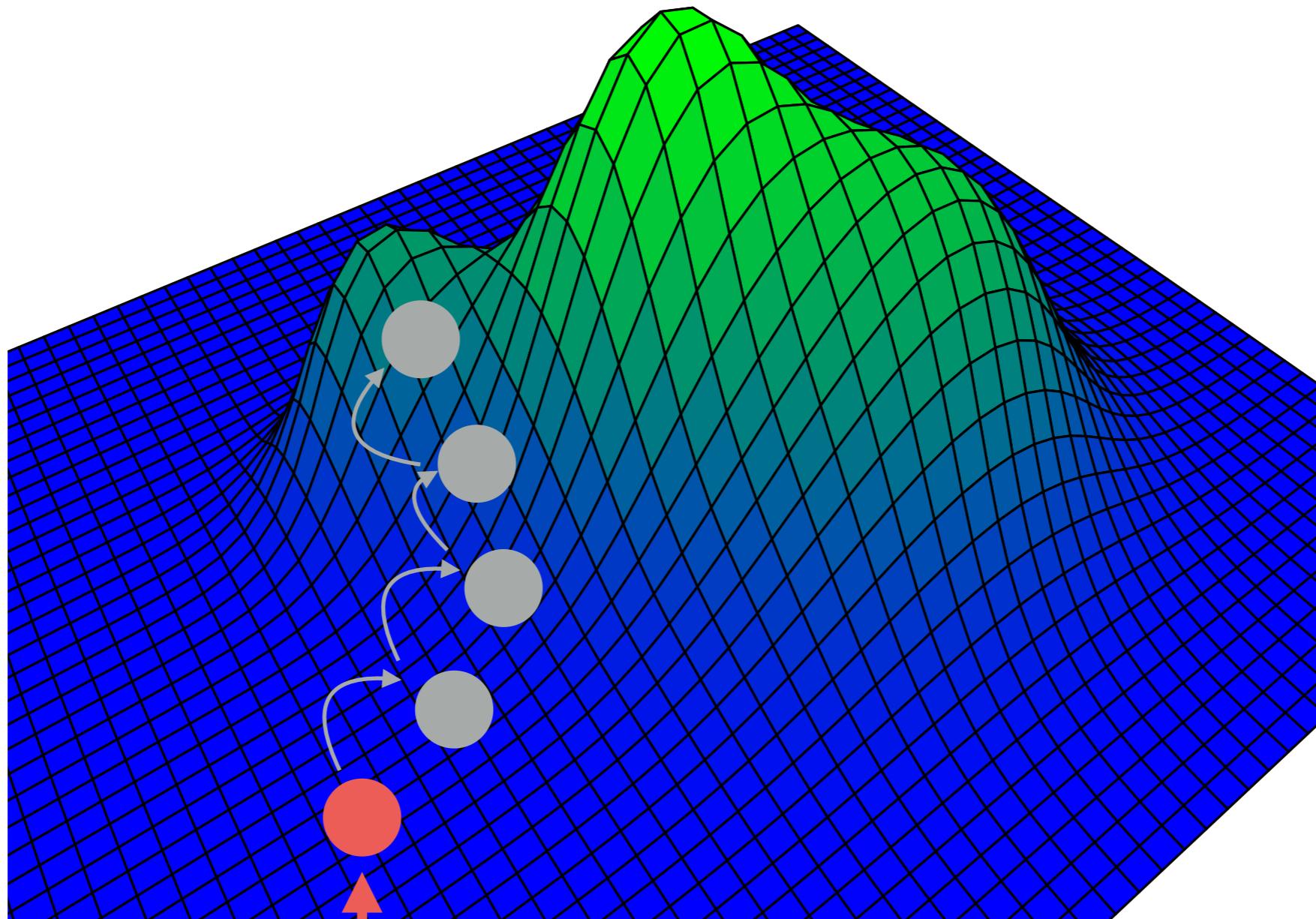
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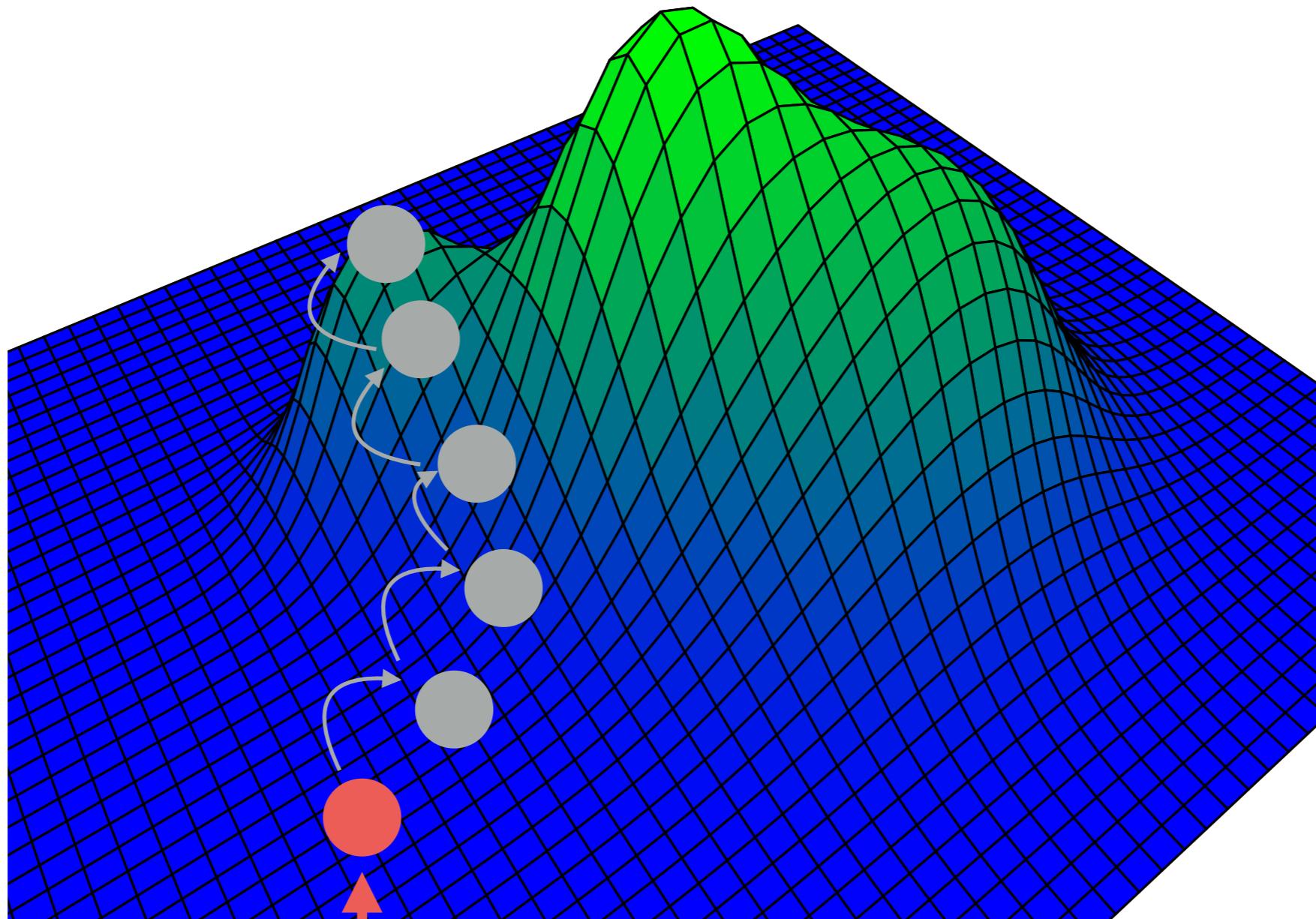
Starting tree

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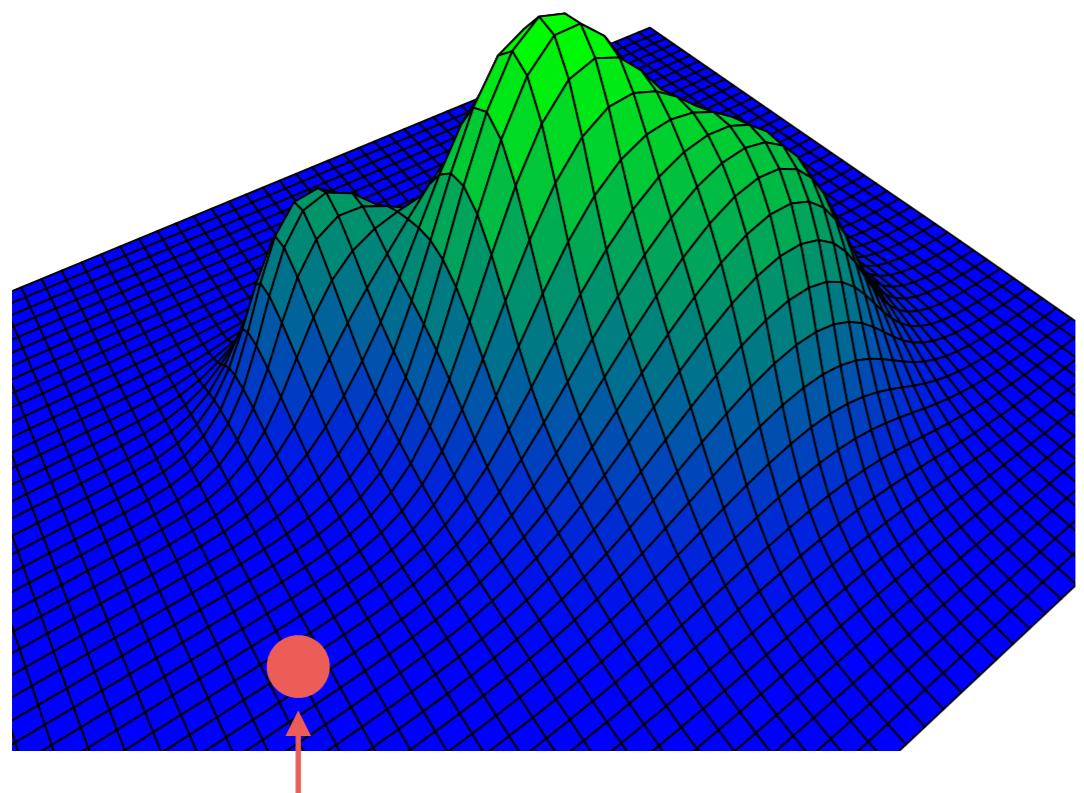
Starting tree

Why is MCMC so slow? Traverse tree space

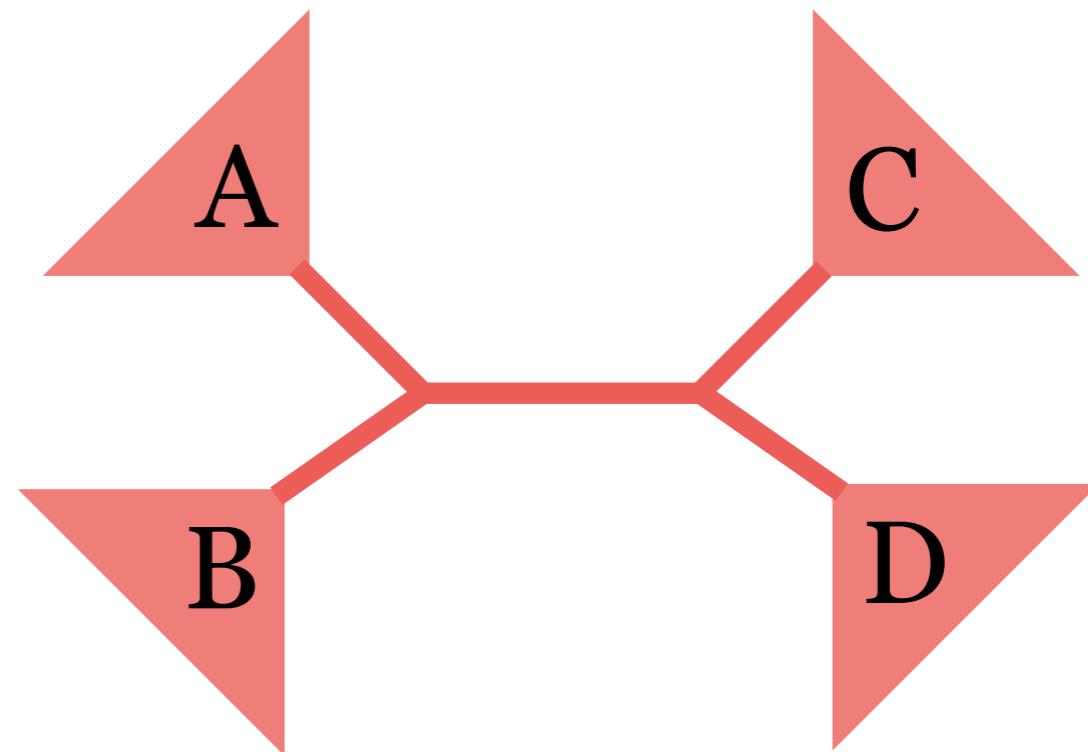


Starting tree

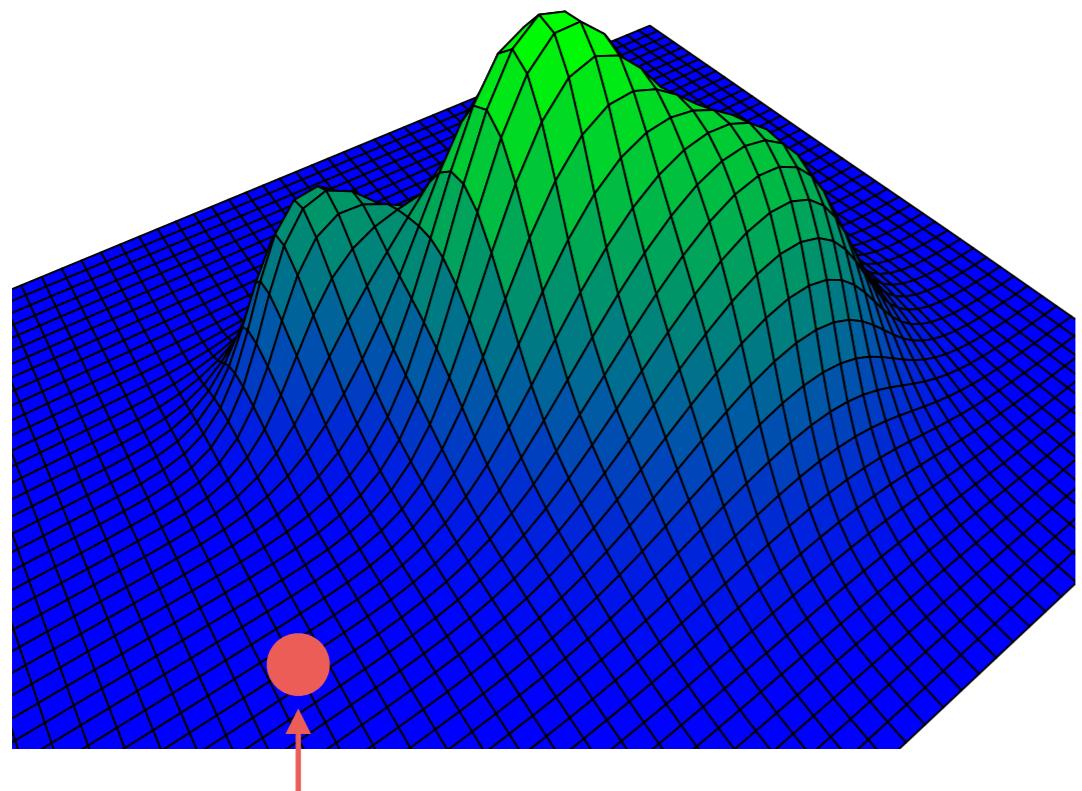
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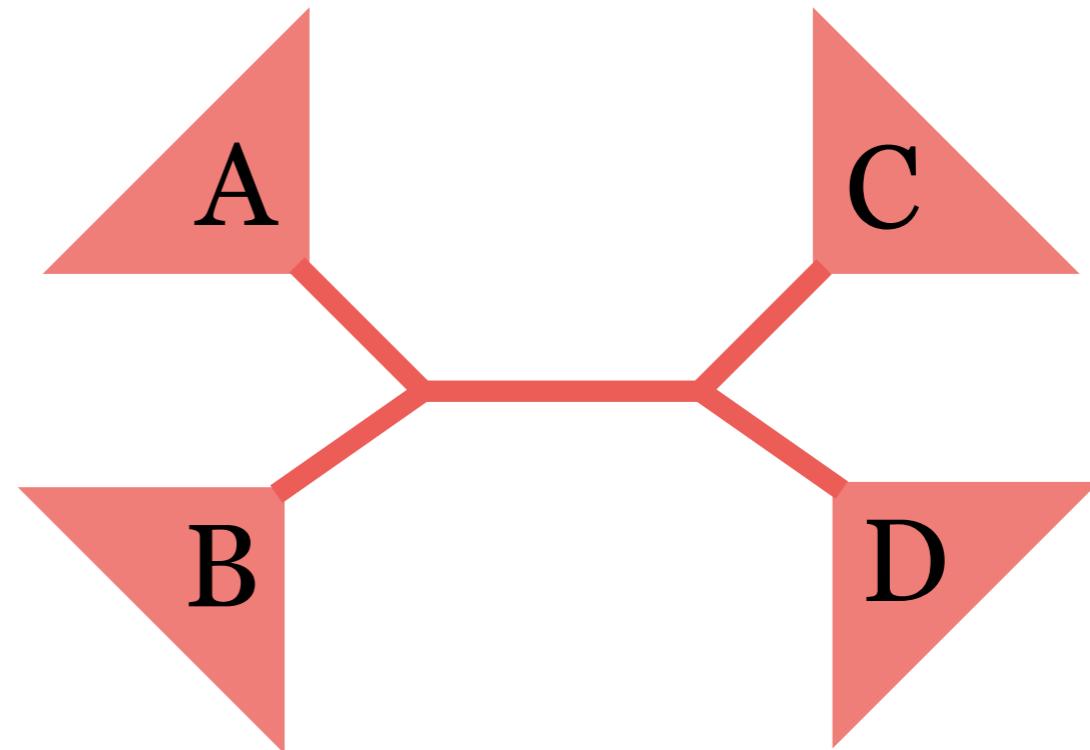
Starting tree



Why is MCMC so slow? Traverse tree space

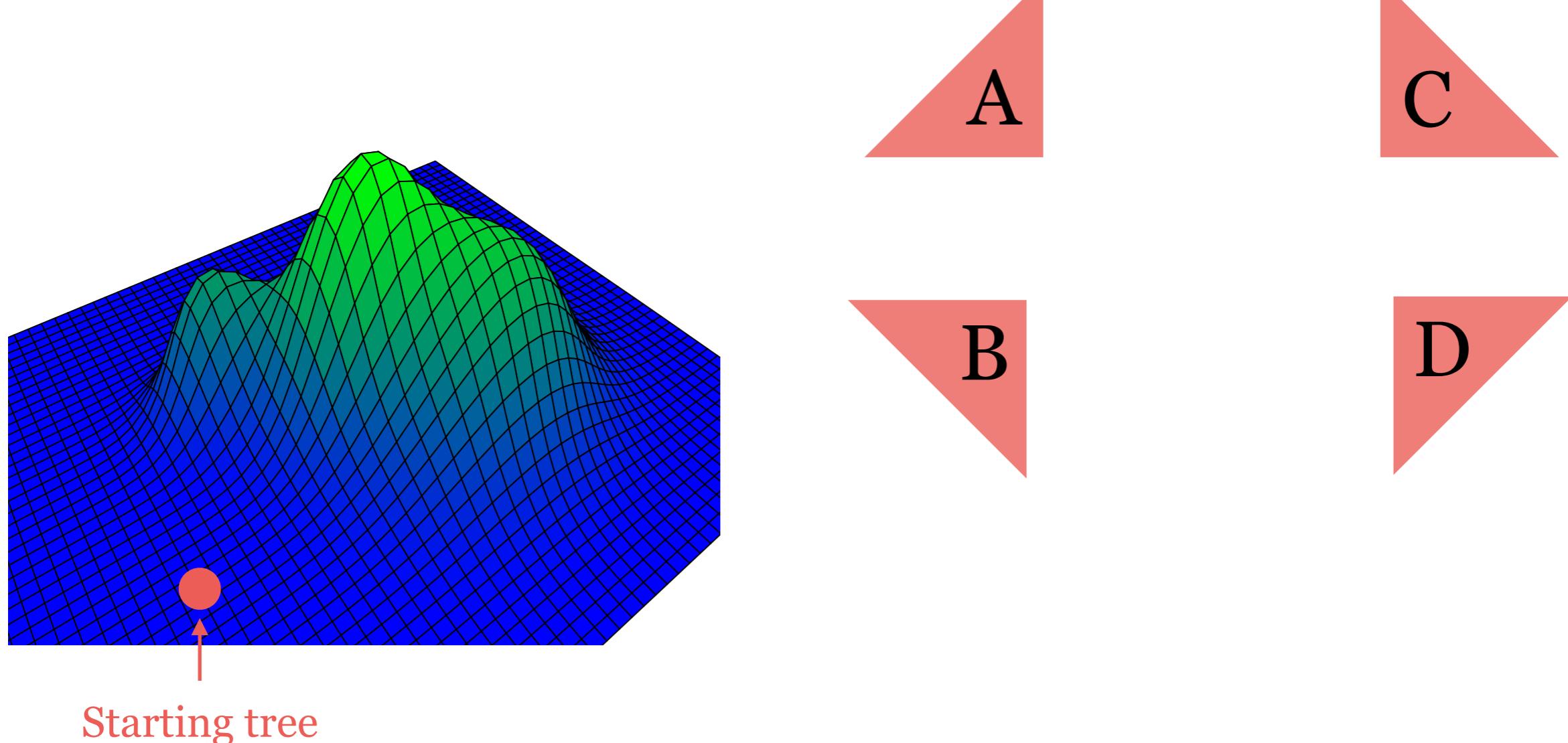


Starting tree



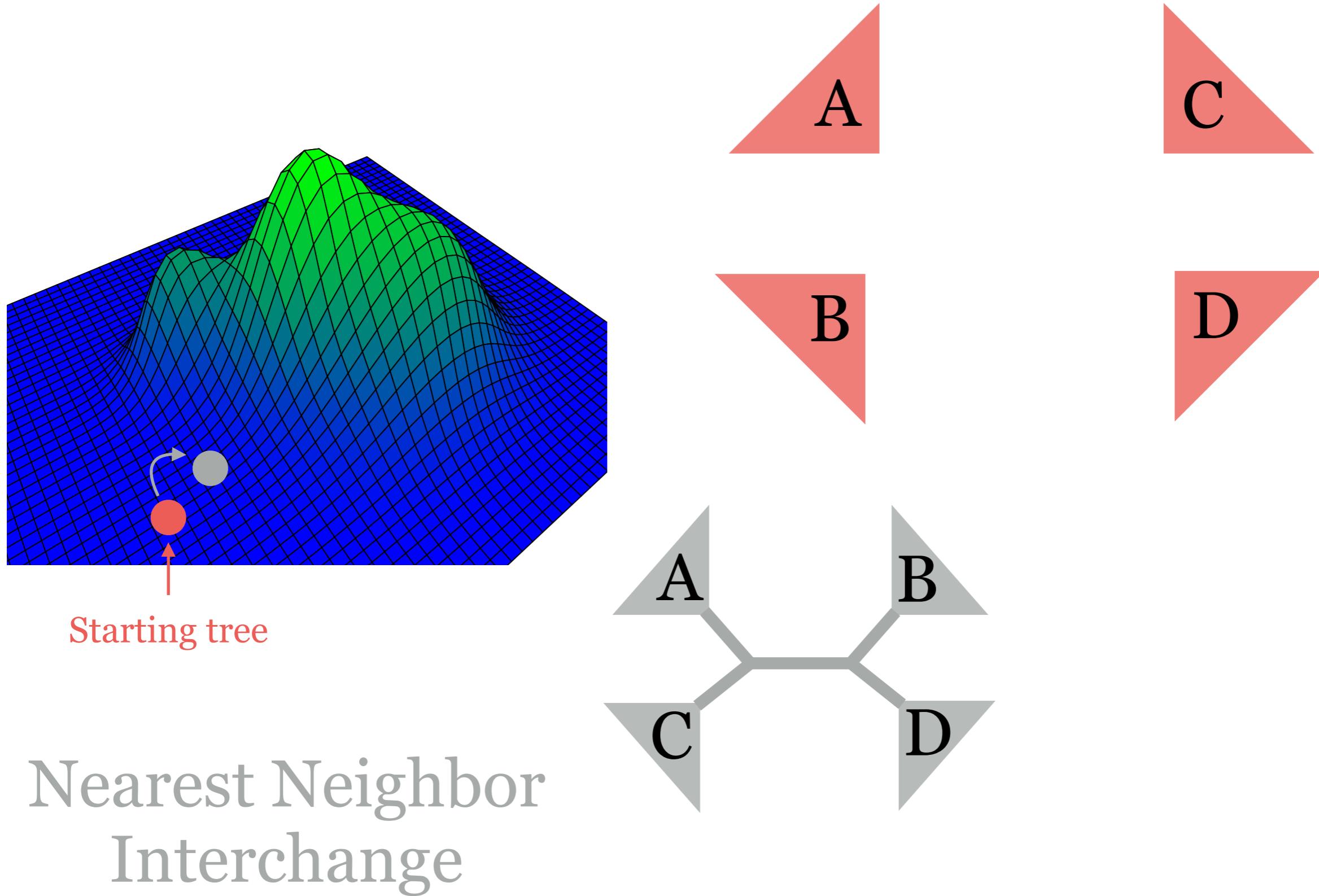
Nearest Neighbor
Interchange

Why is MCMC so slow? Traverse tree space

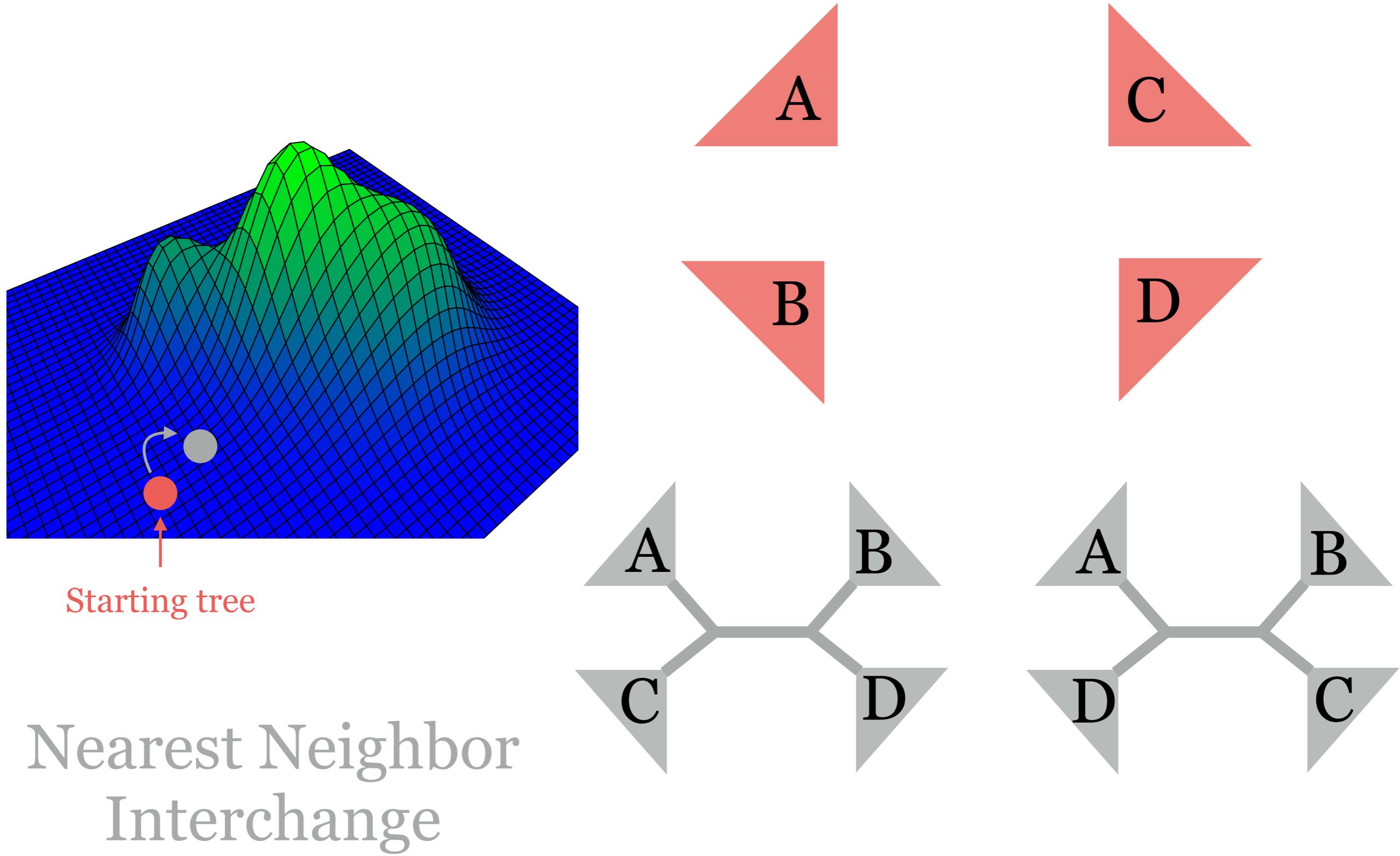


Nearest Neighbor
Interchange

Why is MCMC so slow? Traverse tree space



Why is MCMC so slow? Traverse tree space



Why is MCMC so slow?

Why is MCMC so slow? Tree space is huge

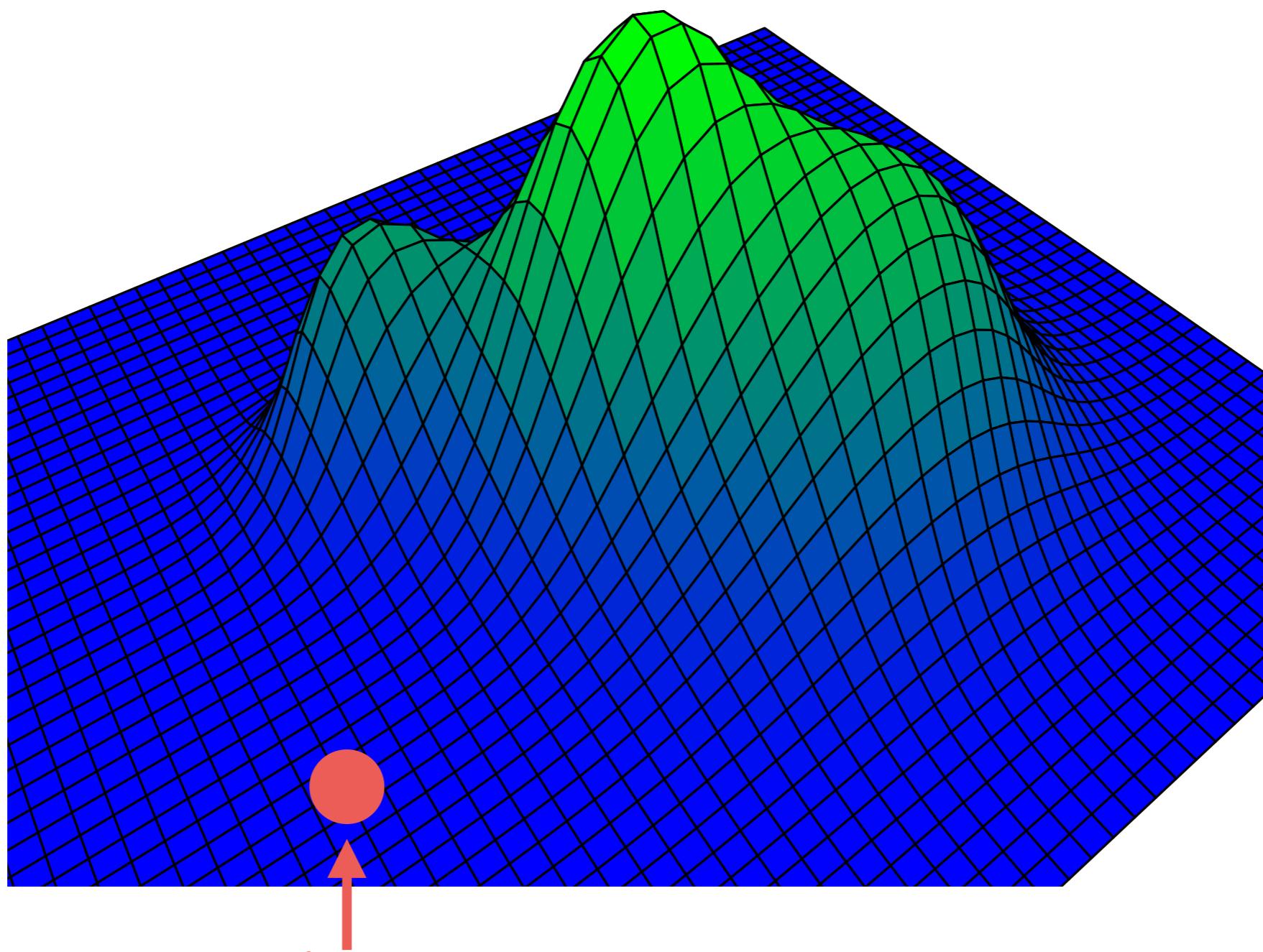
Why is MCMC so slow? Tree space is huge

# Species	# Unrooted trees	# Rooted trees
1	1	1
2	1	1
3	1	3
4	3	15
5	15	105
6	105	945
7	945	10395
8	10,395	135,135
9	135,135	2,027,025
10	2,027,025	34,459,425
11	34,459,425	654,729,075
12	654,729,075	13,749,310,575
13	13,749,310,575	316,234,143,225
:	:	:
52	> # atoms in universe	

Why is MCMC so slow?

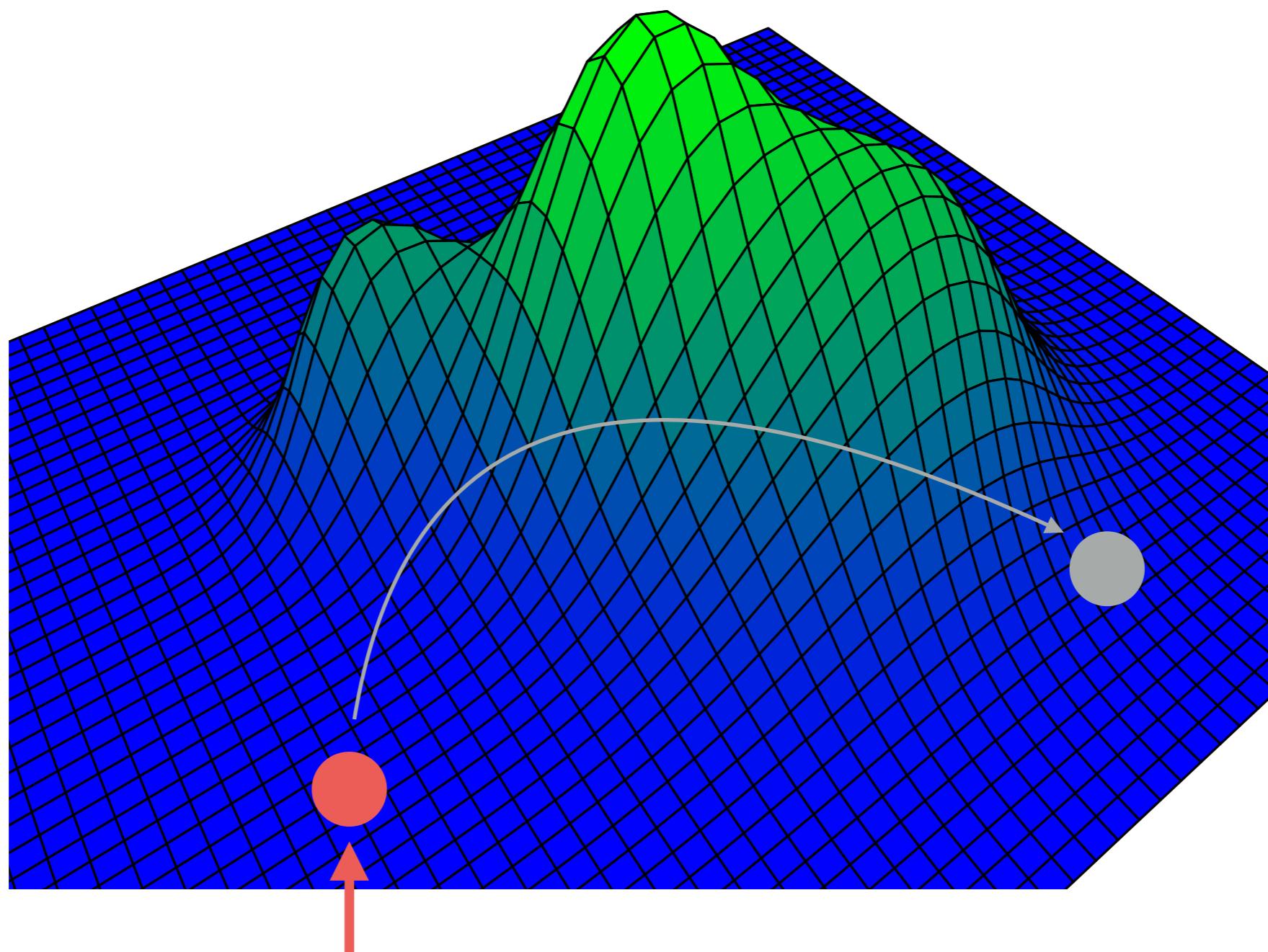
Why is MCMC so slow? Low acceptance of moves

Why is MCMC so slow? Low acceptance of moves



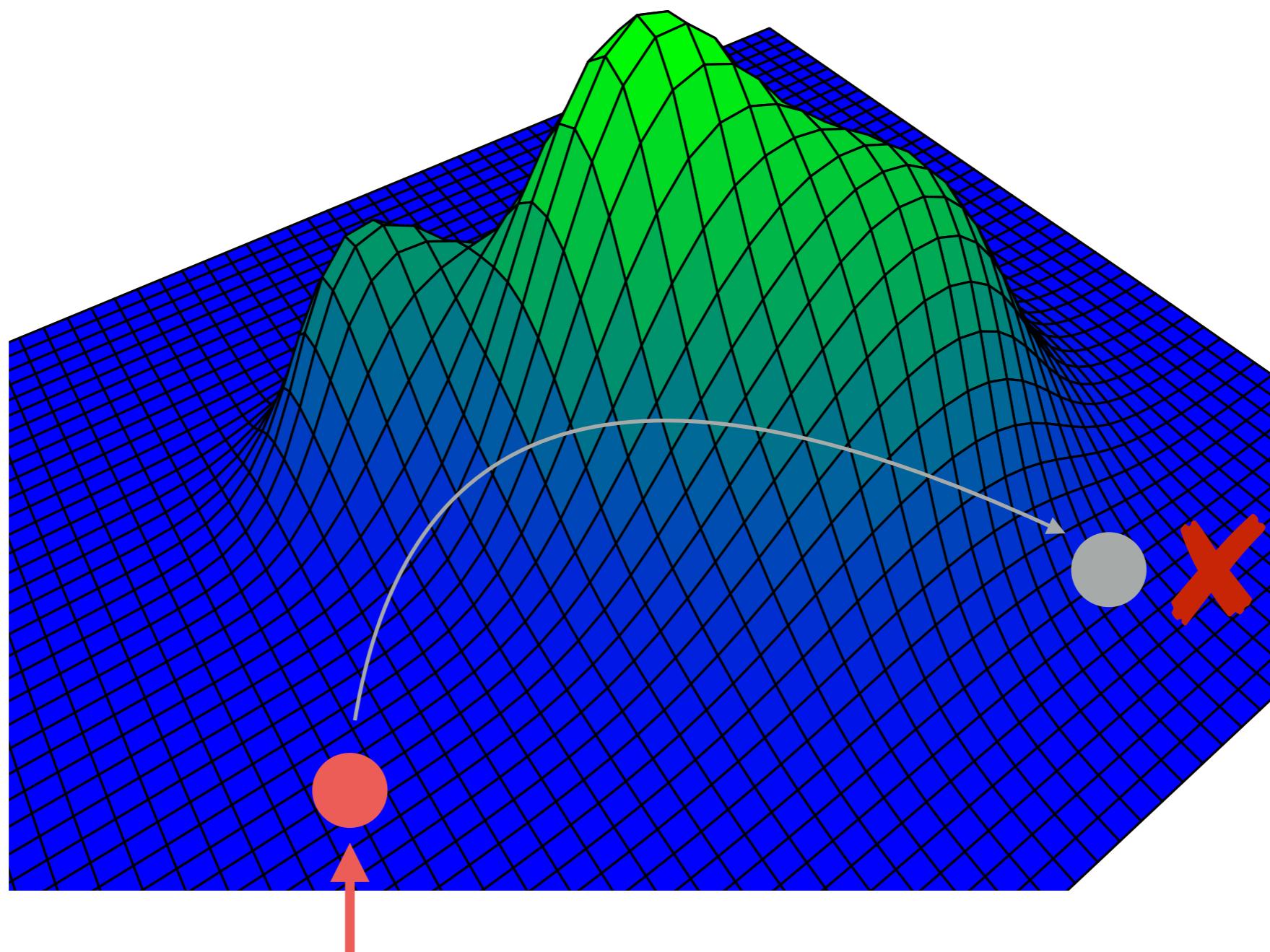
Starting tree

Why is MCMC so slow? Low acceptance of moves



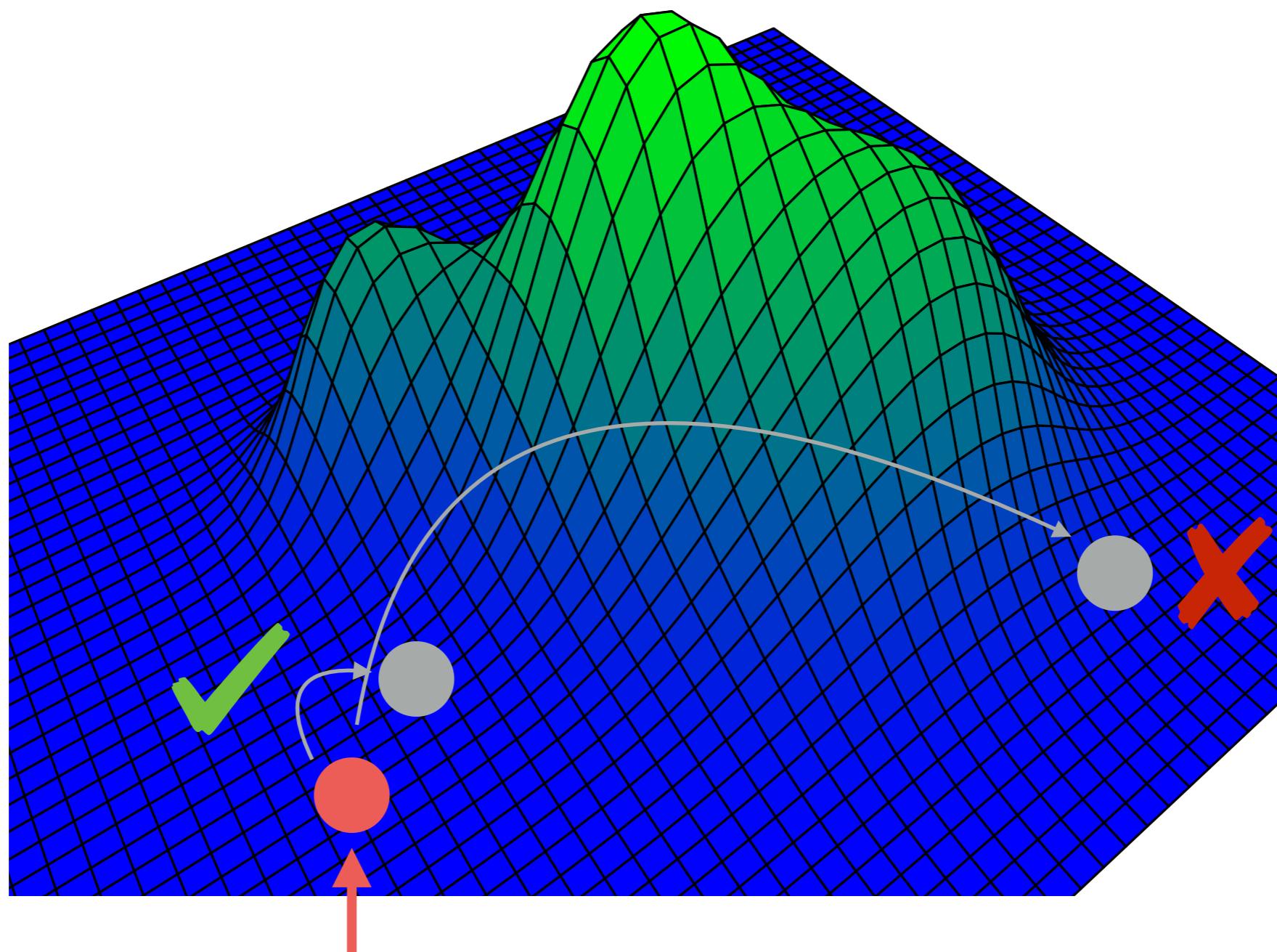
Starting tree

Why is MCMC so slow? Low acceptance of moves



Starting tree

Why is MCMC so slow? Low acceptance of moves



Starting tree

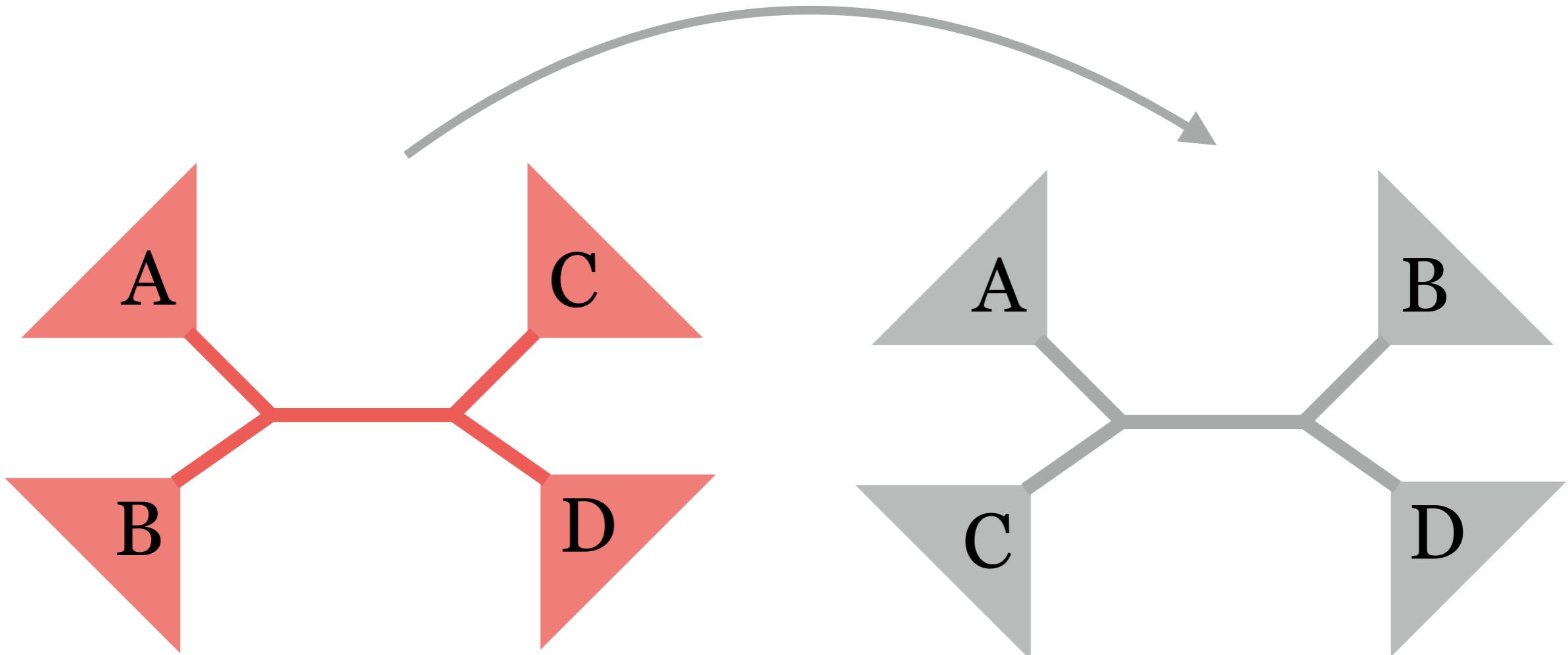
Why is MCMC so slow?

Why is MCMC so slow?

Small neighborhood
implies very dependent
sample

Why is MCMC so slow?

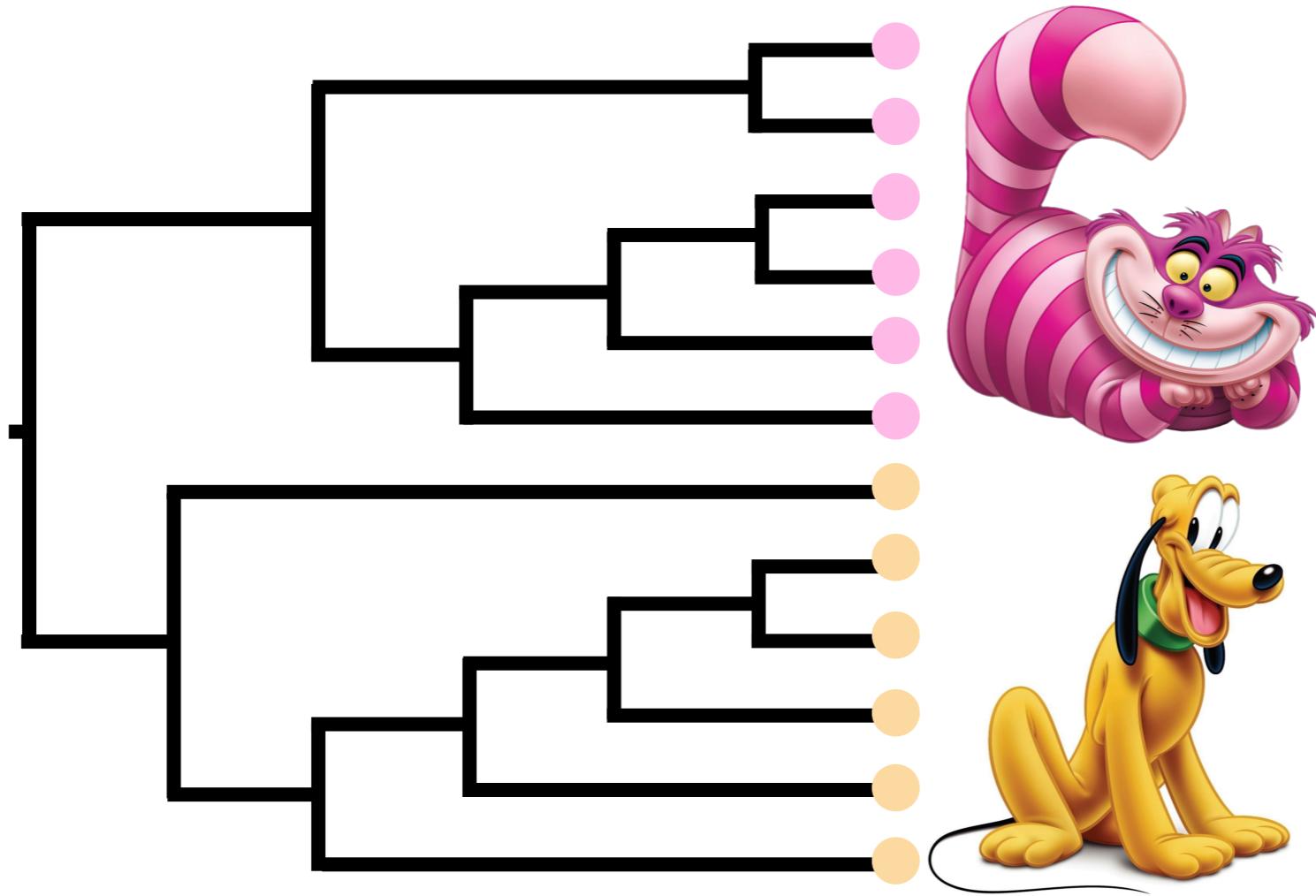
Small neighborhood
implies very dependent
sample



Why is MCMC so slow?

- 1) Huge tree space size
- 2) Low acceptance of moves unless small neighborhood
- 3) Small neighborhood implies very dependent sample, which means small effective sample size

We need a gigantic chain because the space is huge and we are making tiny moves



12 taxa *Carnivora*

MCMC efficiency $\sim 0.025\%$

(250 from 1 million post-burnin generations)

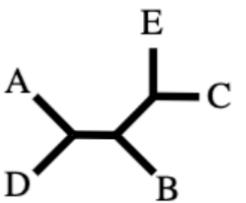
ESS
↑

Priors

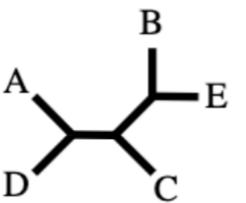
Common Priors

- **Discrete uniform** for topologies
 - exceptions becoming more common
- **Beta** for proportions
- **Gamma** or **Log-normal** for branch lengths and other parameters with support $[0, \infty)$
 - Exponential is common special case of the gamma distribution
- **Dirichlet** for state frequencies and GTR relative rates

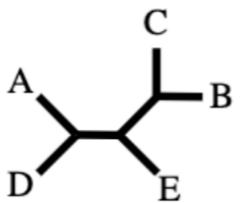
Discrete Uniform distribution for topologies



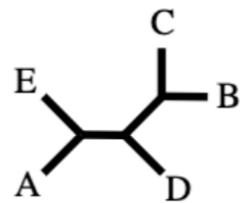
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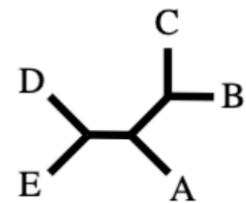
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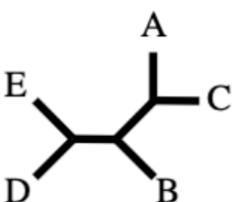
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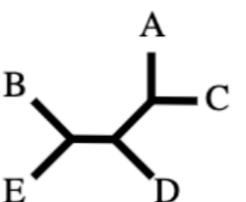
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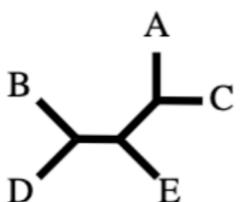
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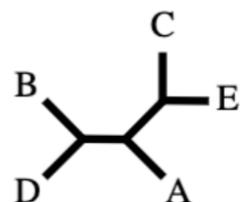
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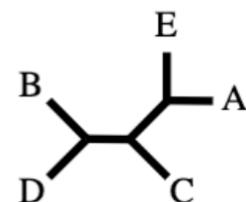
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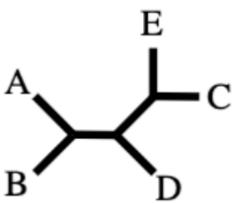
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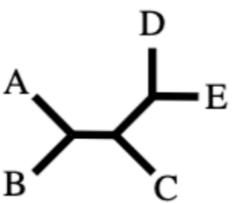
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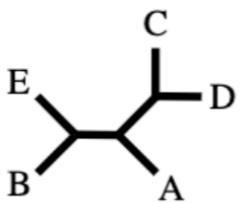
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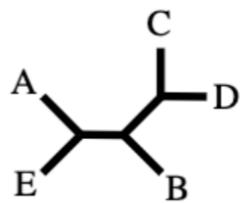
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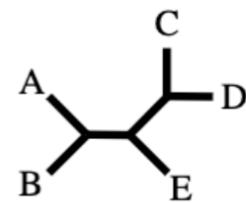
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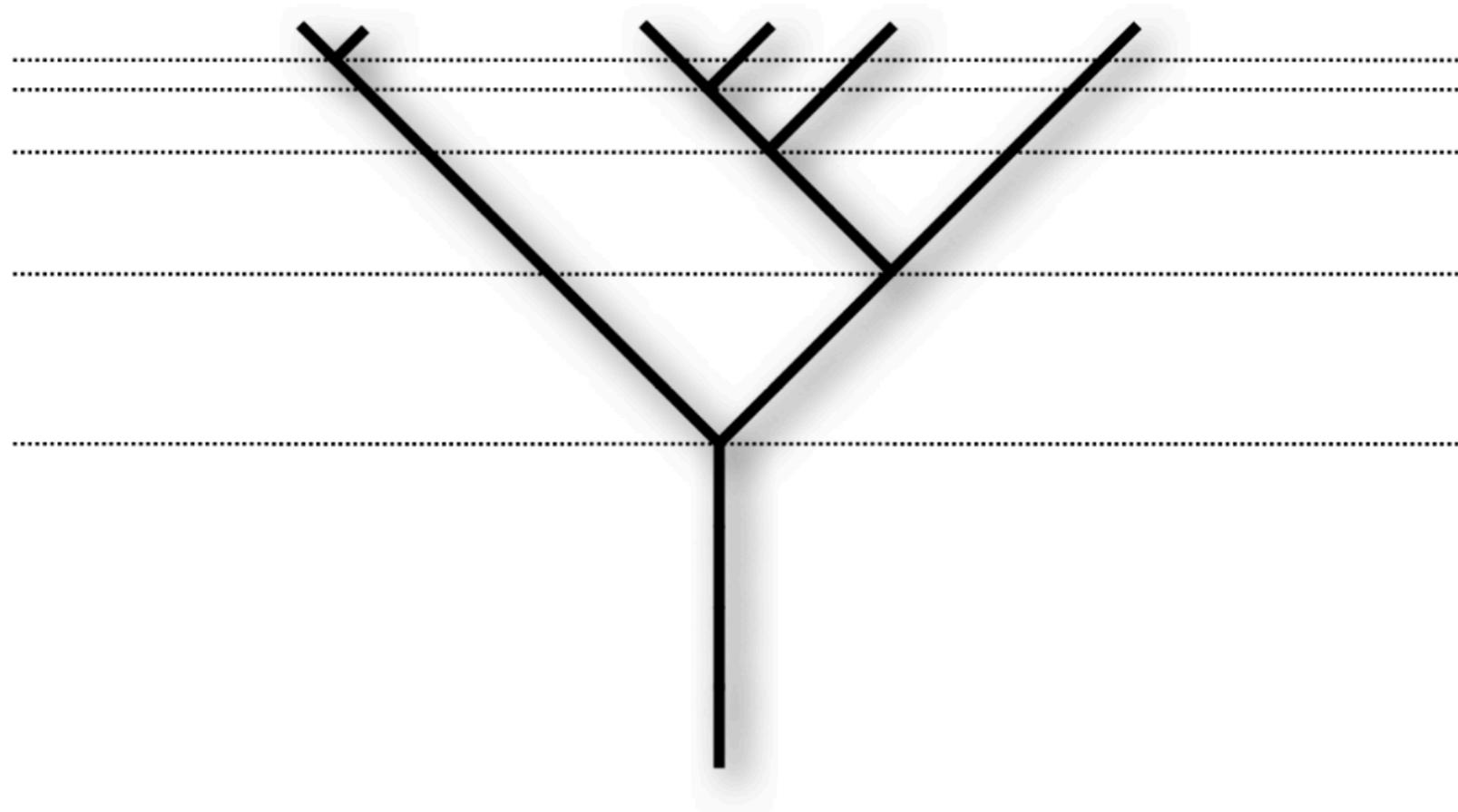


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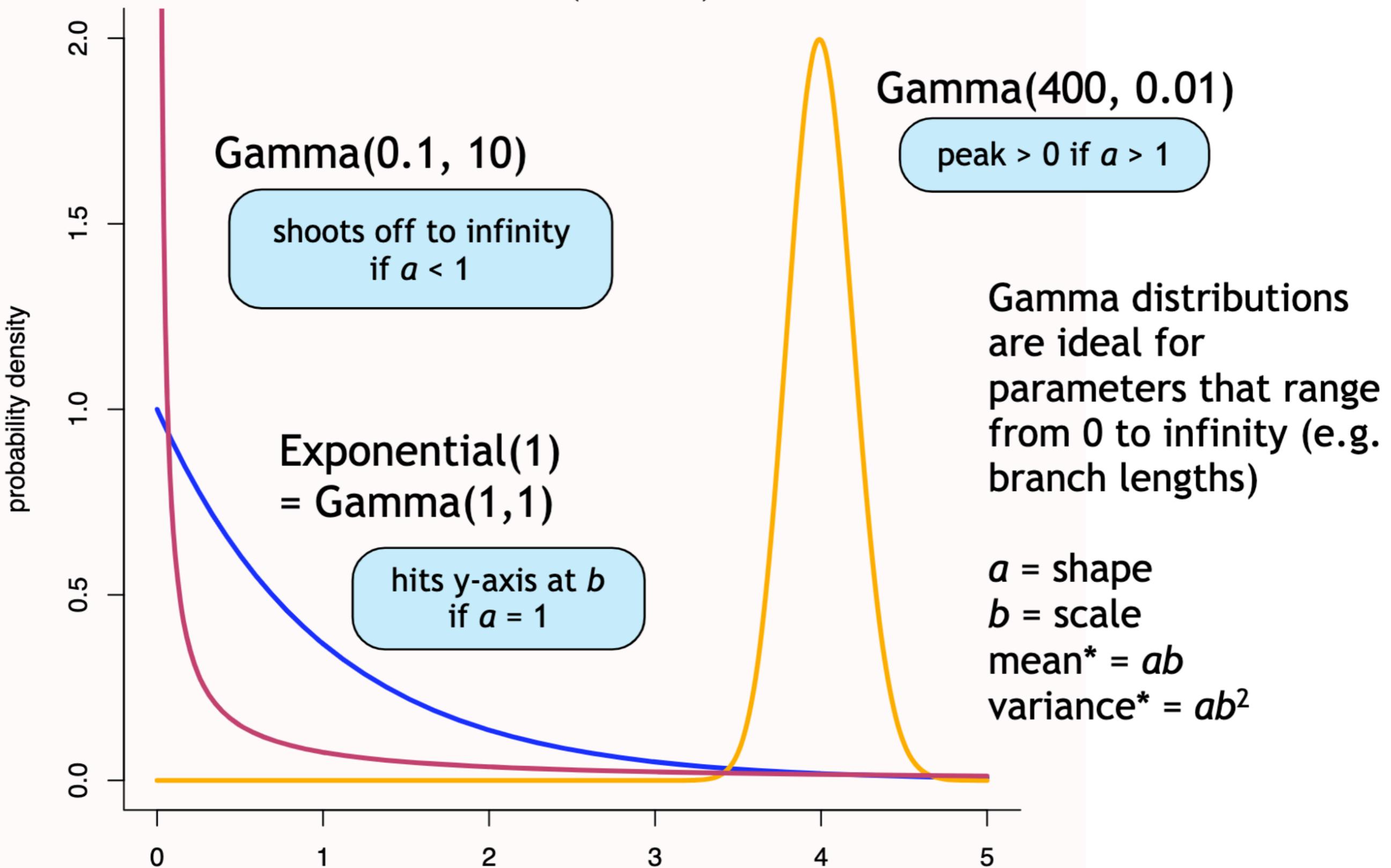
1
15

Yule model provides joint prior for both topology and divergence times



The rate of speciation under the Yule model (λ) is constant and applies equally and independently to each lineage. Thus, speciation events get closer together in time as the tree grows because more lineages are available to speciate.

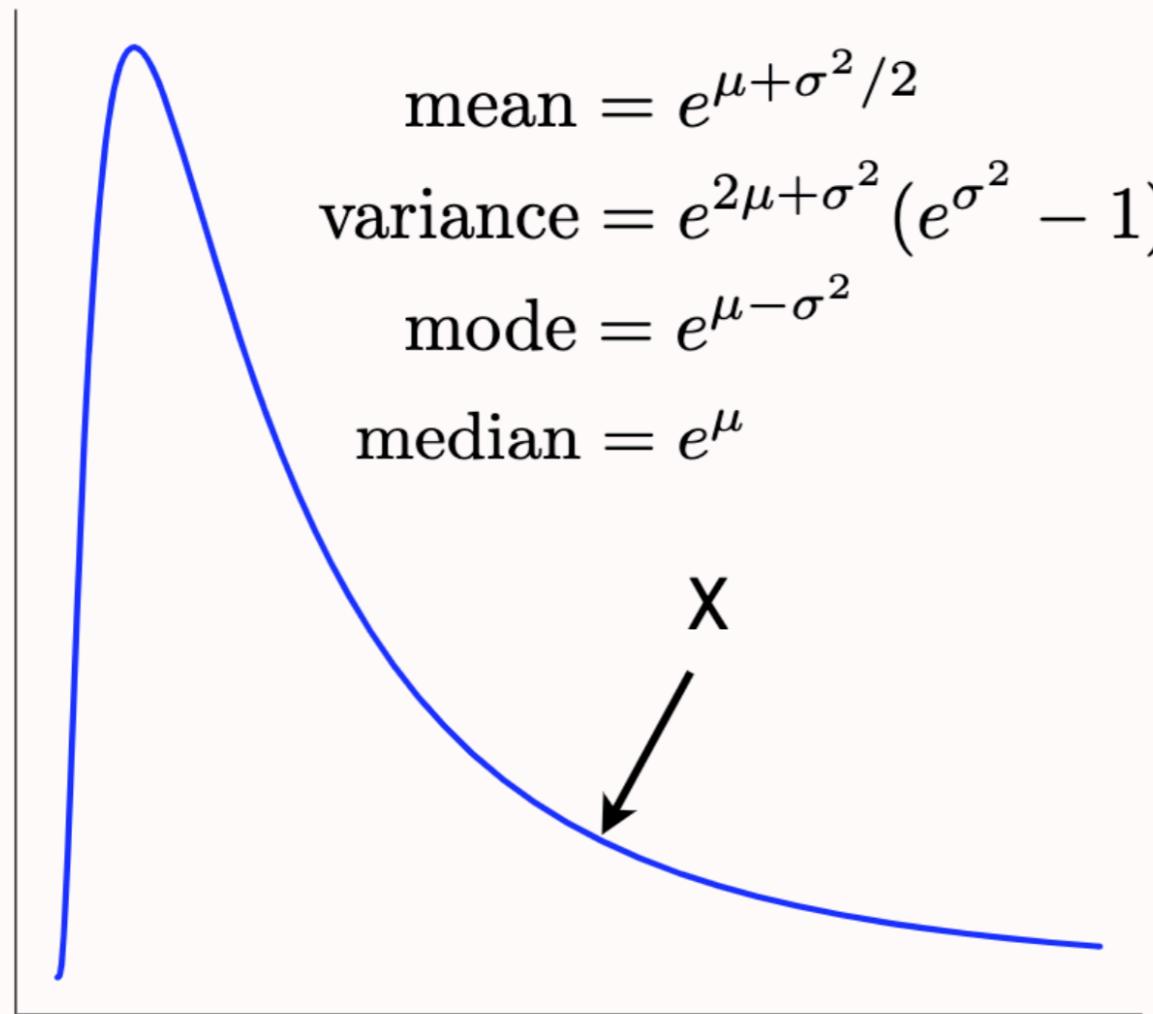
Gamma(a, b) distributions



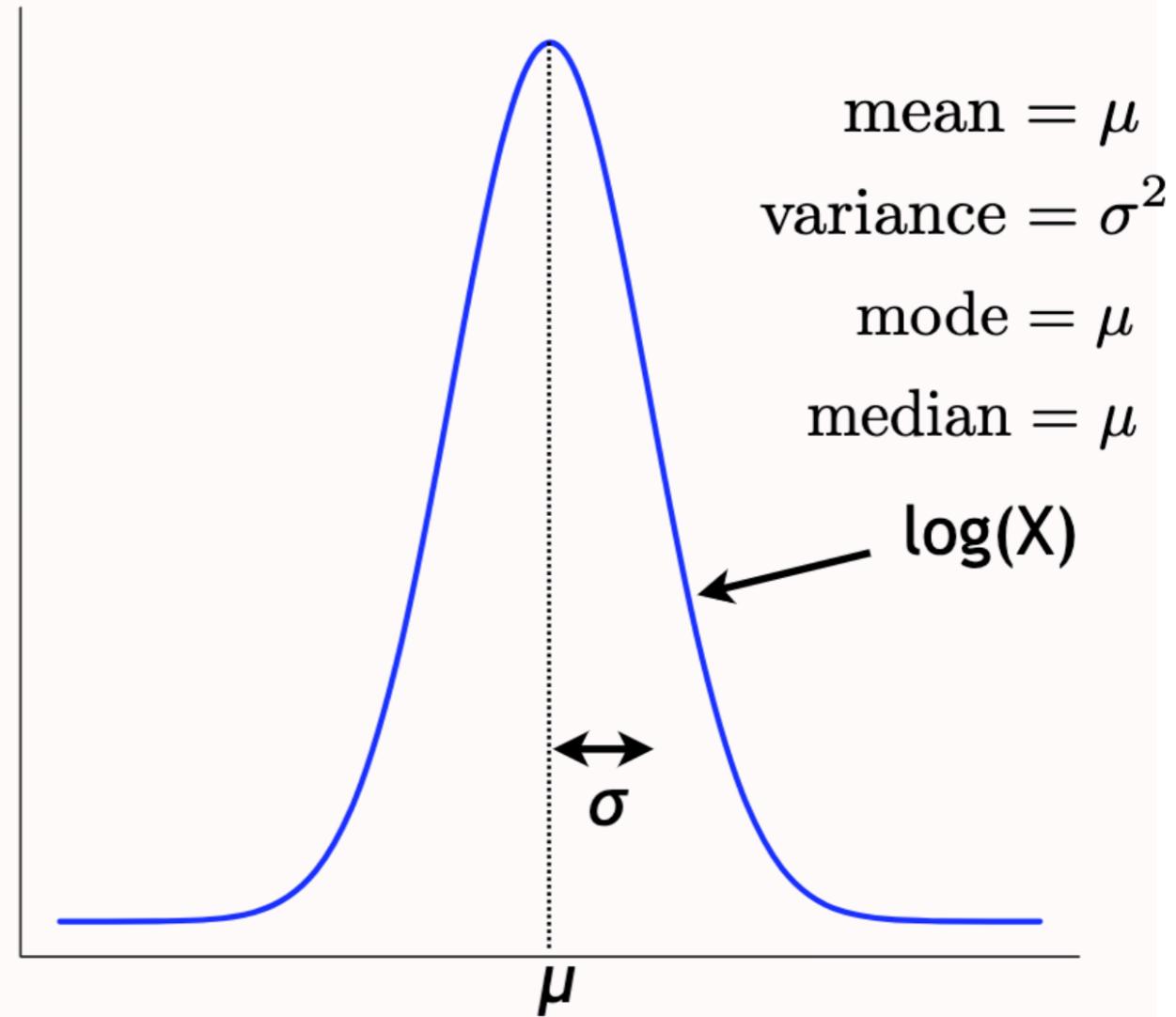
*Note: be aware that in many papers the Gamma distribution is defined such that the second (scale) parameter is the *inverse* of the value b used in this slide! In this case, the mean and variance would be a/b and a/b^2 , respectively.

Log-normal distribution

If X is log-normal with *parameters* μ and σ ...



...then $\log(X)$ is normal with *mean* μ and *standard deviation* σ .

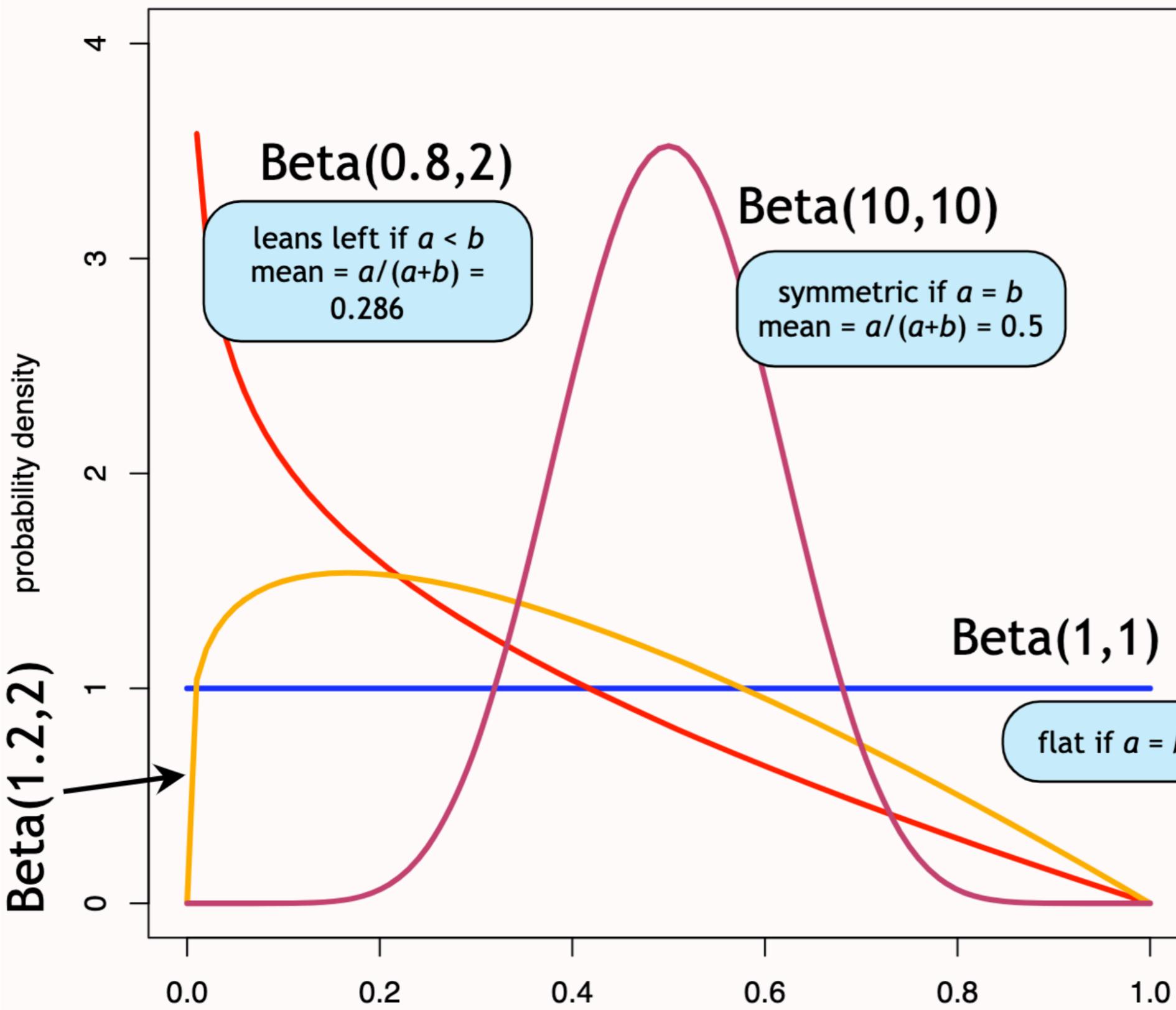


Important: μ and σ do **not** represent the mean and standard deviation of X : they are the mean and standard deviation of $\log(X)$!

To choose μ and σ to yield a particular mean (m) and variance (v) for X , use these formulas:

$$\mu = \log(m^2) - \log(m) - \frac{\log(v + m^2) - \log(m^2)}{2}$$
$$\sigma^2 = \log(v + m^2) - \log(m^2)$$

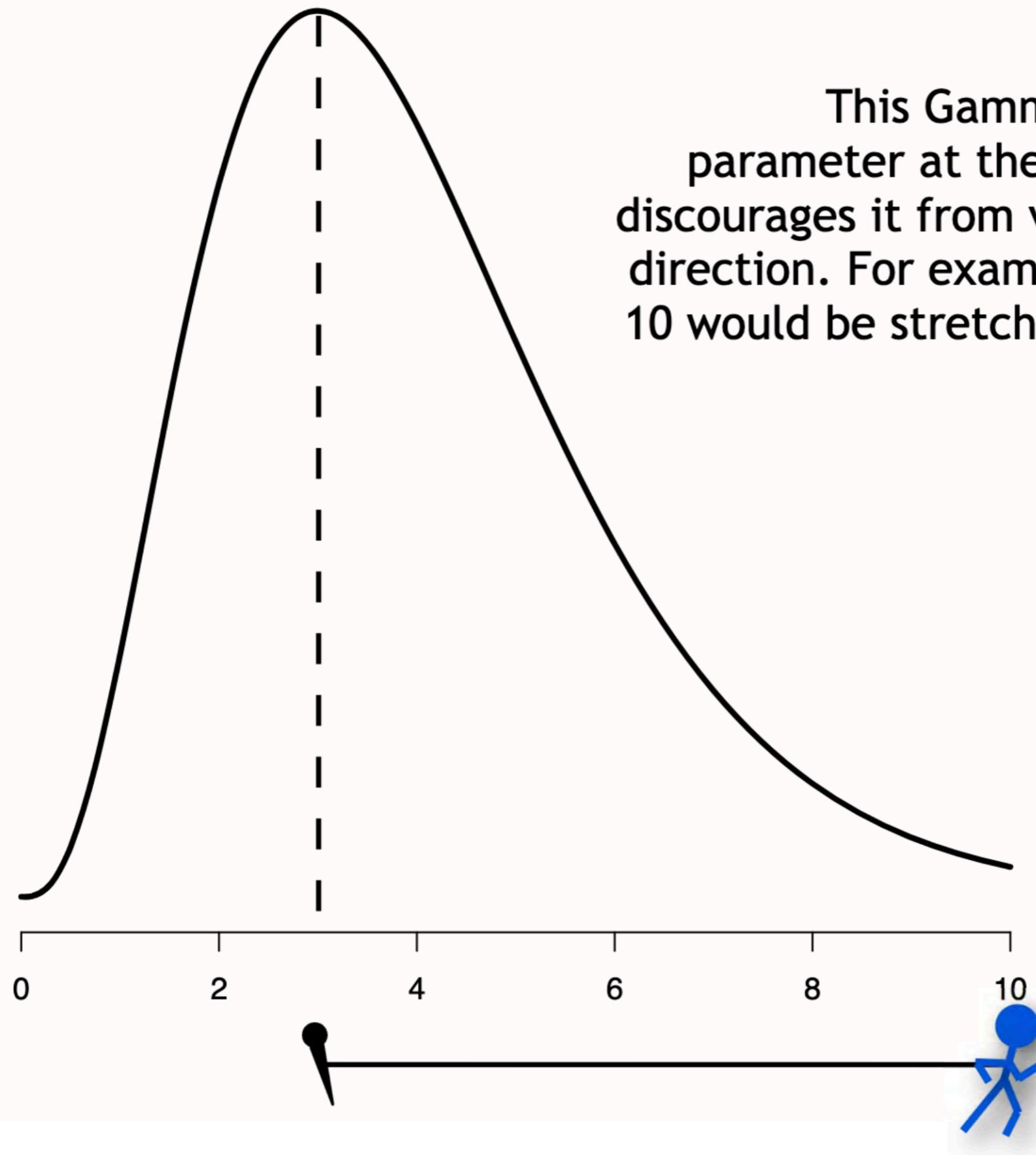
Beta(a,b) gallery



Beta distributions are appropriate for proportions, which are constrained to the interval [0,1].

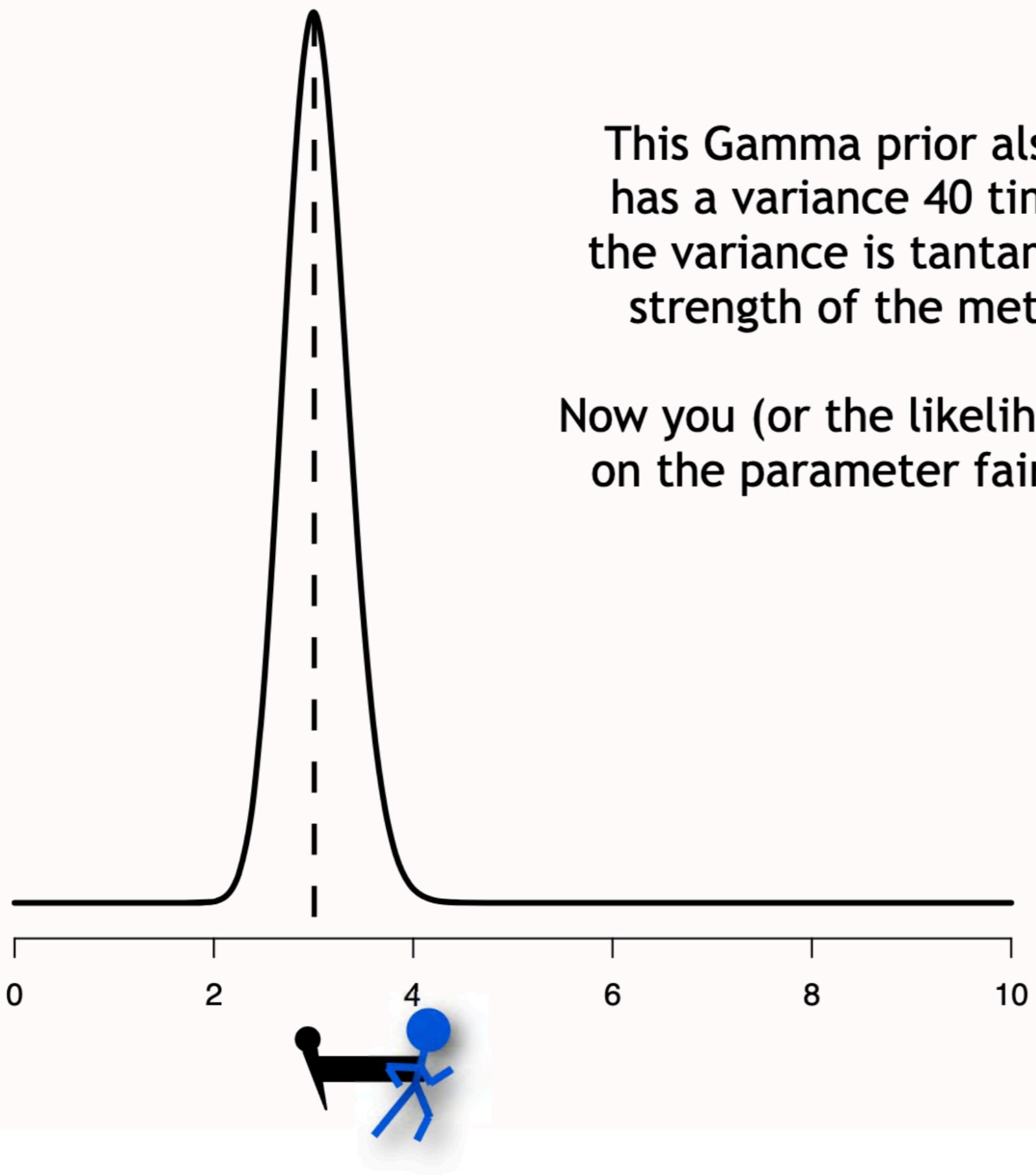
$$\text{mean} = a/(a+b)$$
$$\text{variance} = ab/[(a+b)^2(a+b+1)]$$

Non-informative prior

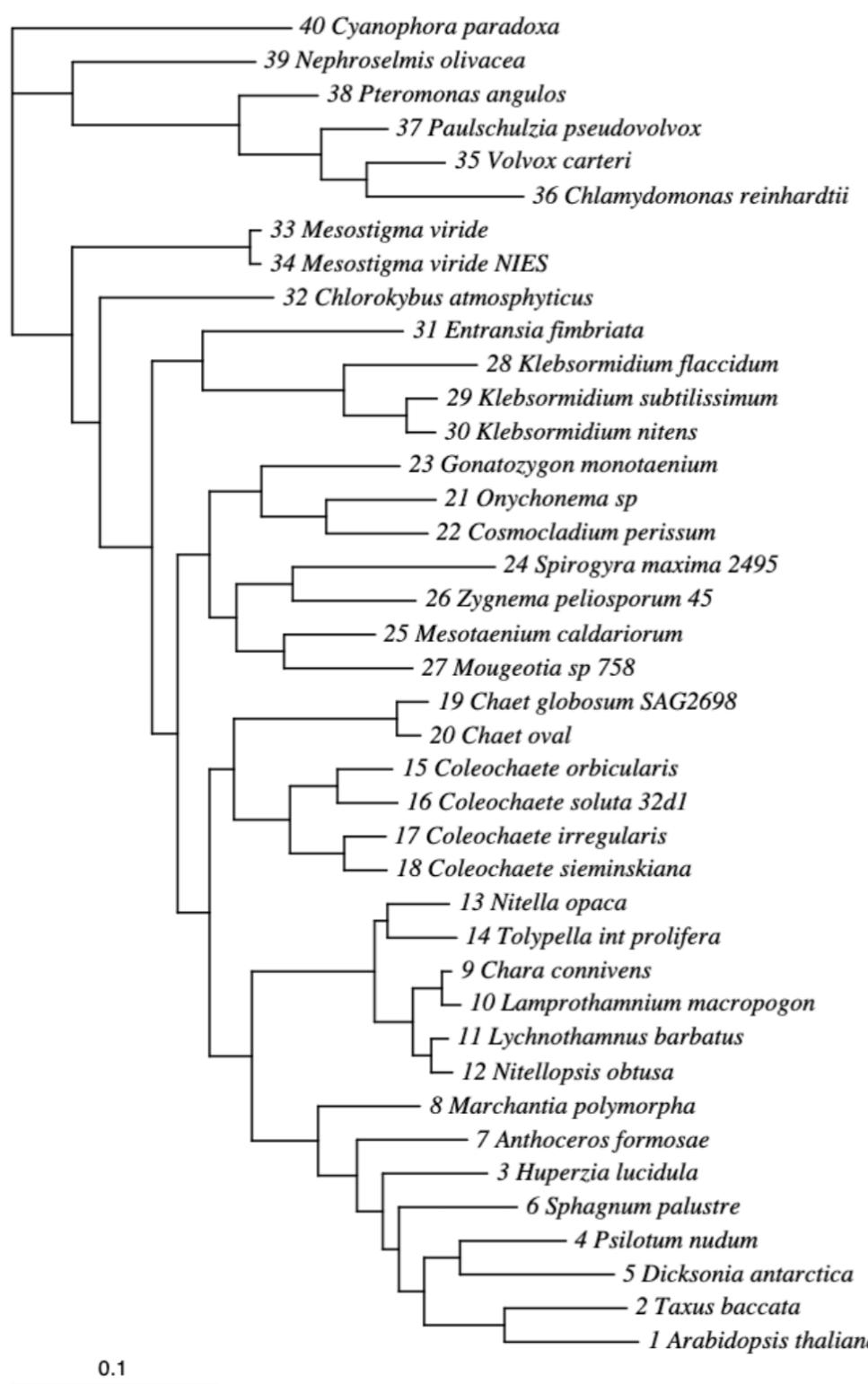


This Gamma(4,1) prior ties down its parameter at the mode, which is at 3, and discourages it from venturing too far in either direction. For example, a parameter value of 10 would be stretching the rubber band fairly tightly

The mode of a Gamma(a,b) distribution is $(a-1)b$ (assuming $a > 1$)



Example: Internal Branch Length Priors

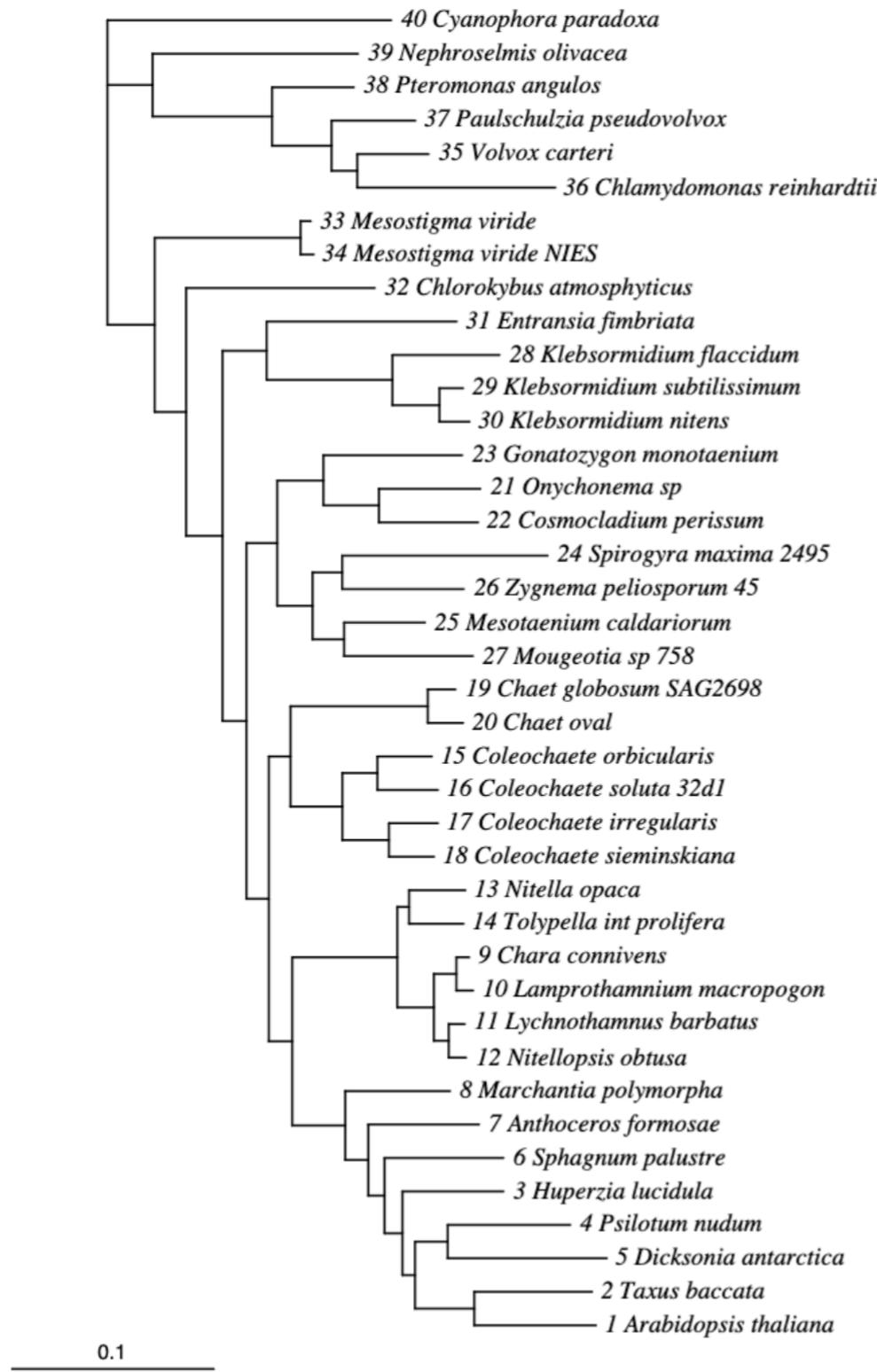


Separate priors applied to internal and external branches

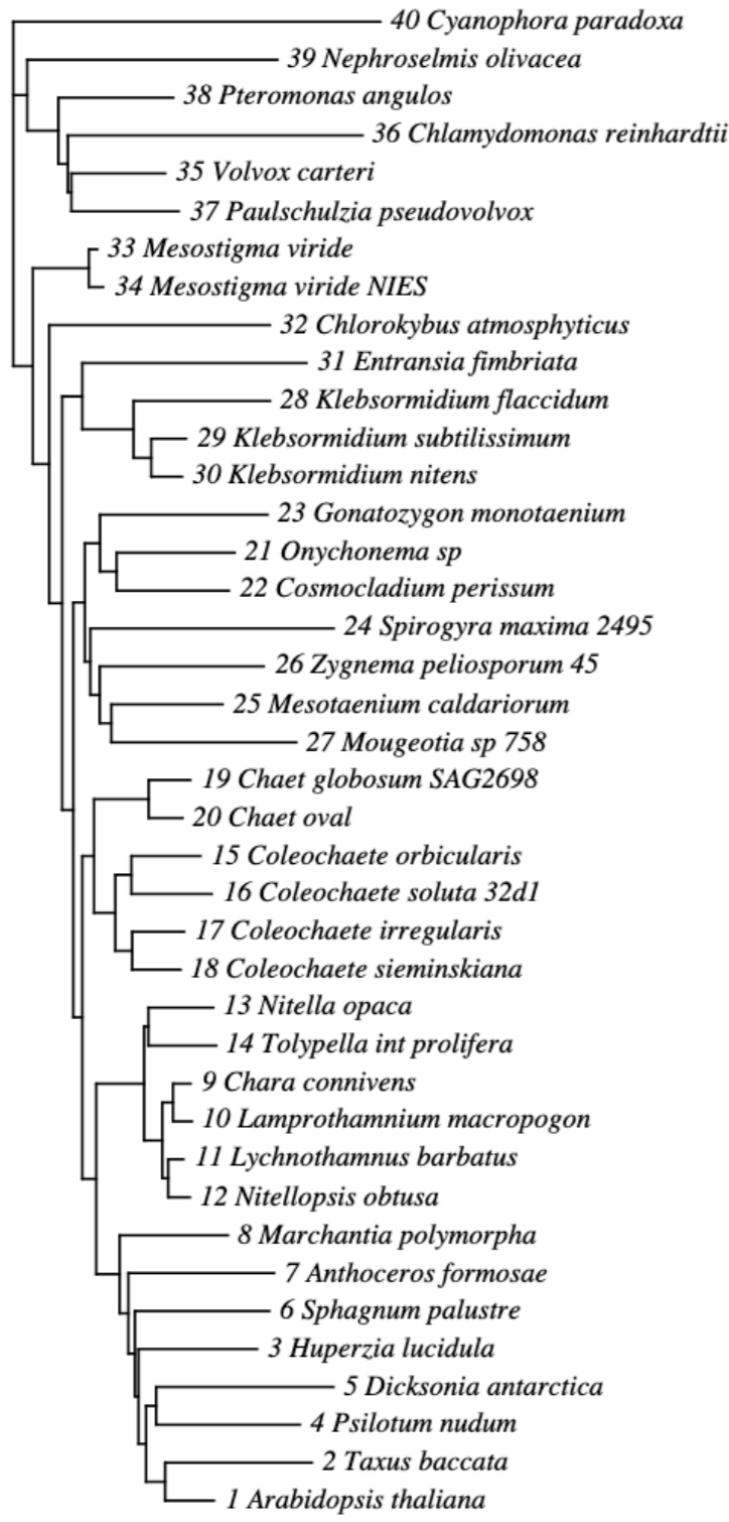
External branch length prior is exponential with mean 0.1

Internal branch length prior is exponential with mean 0.1

This is a reasonably vague internal branch length prior

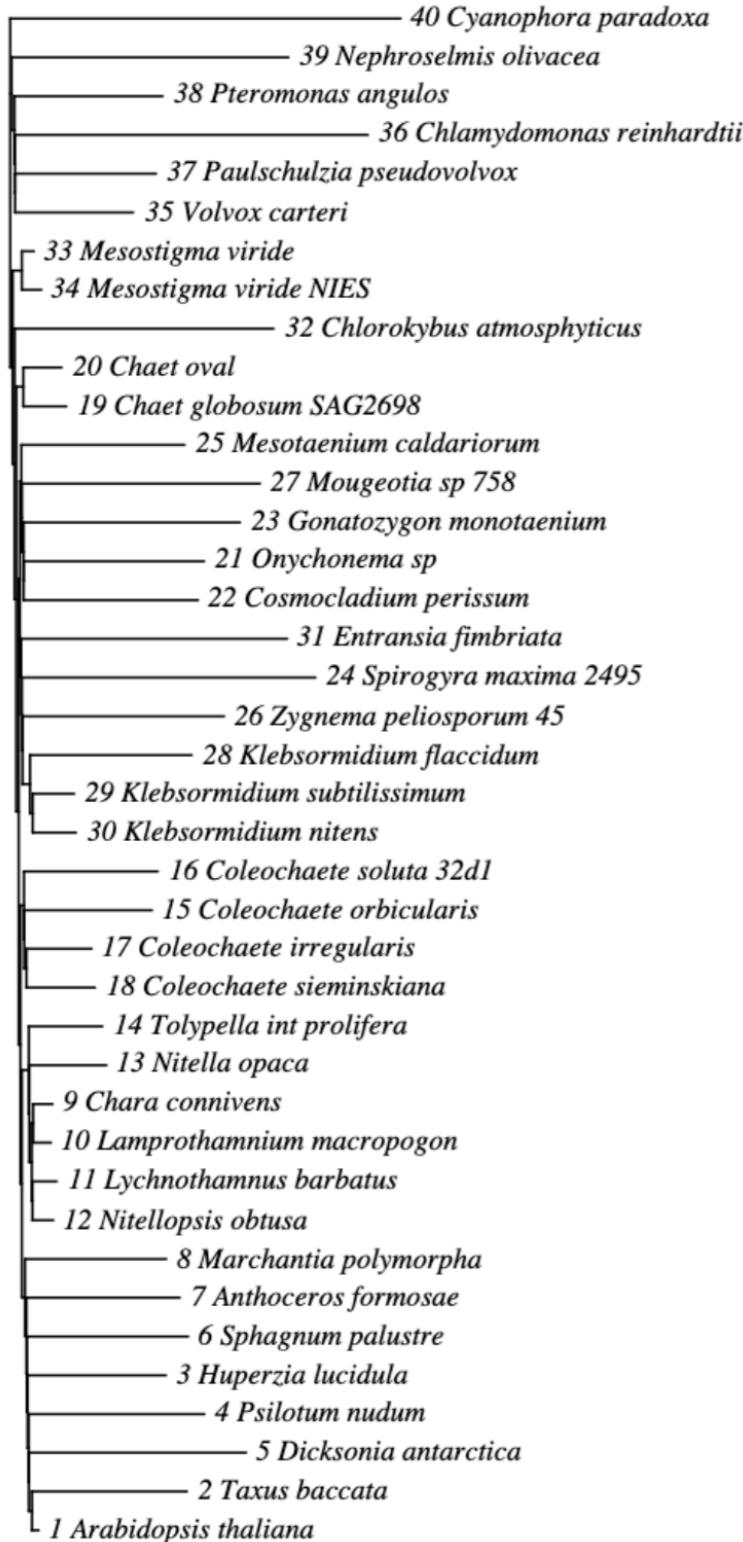


Internal branch length prior mean 0.001



Internal branch length prior mean
0.0001

0.1



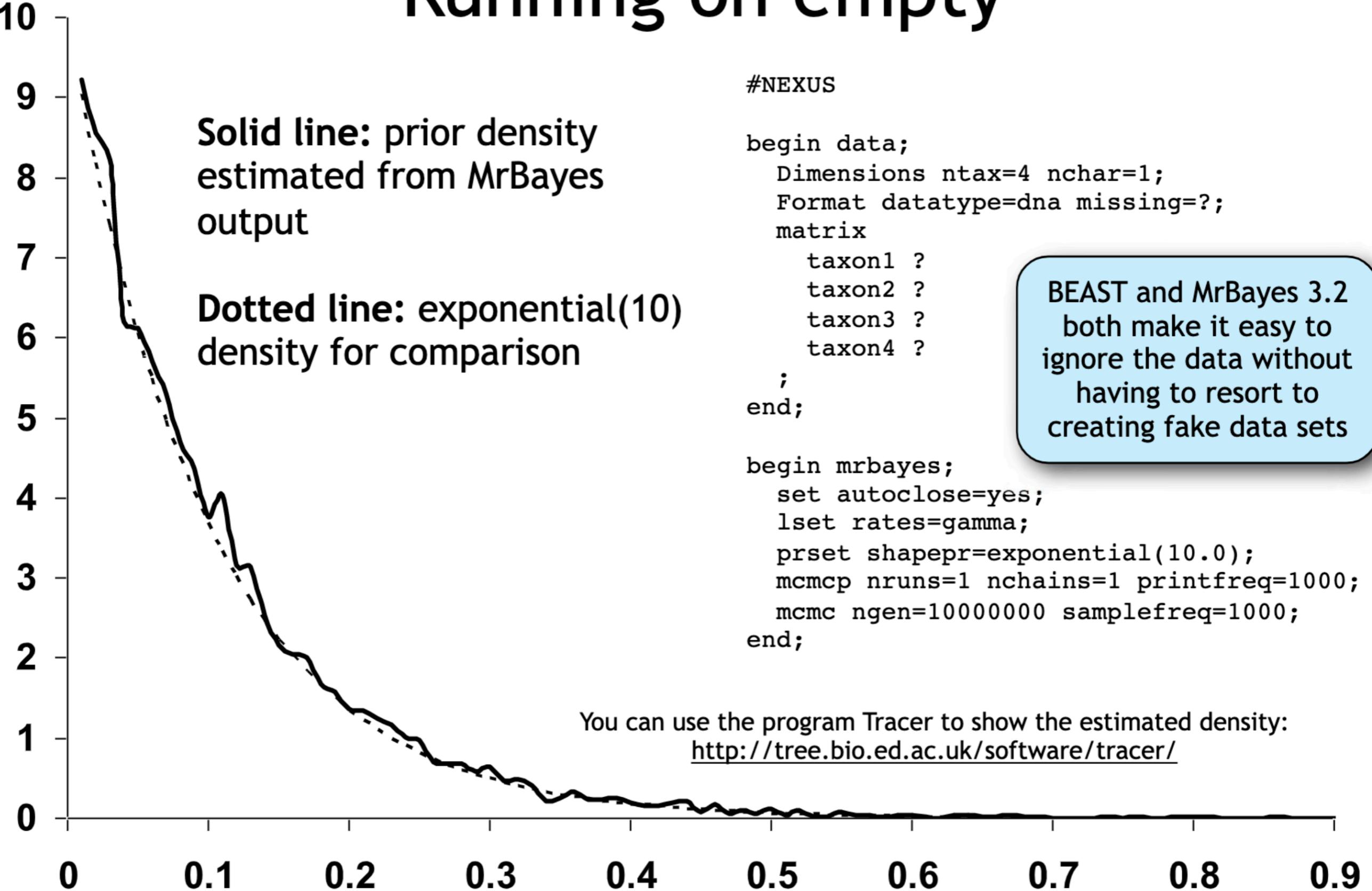
Internal branch length prior mean
0.00001

0.1

Running on empty

- Run MCMC without data
- Some programs generate dummy “empty” alignments that can be used
- Why run MCMC on the prior?
 - Check correctness of the software (do the results match the theoretical prior?)
 - Compare prior run with posterior run:
 - If prior and posterior are too similar, then data might contain little information
 - If prior and posterior overlap, but the posterior is more concentrated, then data are informative and prior is reasonable
 - If prior and posterior do not overlap well, then the prior might be misspecified
- CAUTION: do not set a prior to match the posterior! The prior is meant to reflect our knowledge BEFORE the analysis of the data

Running on empty



In-class dynamic

- **Time:** 20 minutes
- **Instructions:** Choose a software that does bayesian inference and follow the tutorial
 - PhyloBayes: HAL 1.5 ([github repo](#))
 - MrBayes: [tutorial](#)

and create our own reproducible script. **Bonus points** for paying attention to the MCMC considerations that affect performance in the chosen method

- **Disclaimer:** I have not done the steps ahead of time to make sure that everything runs smoothly so that we can troubleshoot this pipeline together
- **Options for you:**
 1. "I think that I can follow the pipeline by myself or with a small group of peers": you should join the Congregate room
 2. "I think I need more one-on-one help to run the commands": you can stay here in the zoom room

Important reading

- Nascimento et al (2017)